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Ko Adachi*
kou.adachi@boj.or.jp

Kosuke Aoki**
kaoki@e.u-tokyo.ac.jp

Yoshiyuki Kurachi***
yoshiyuki.kurachi@boj.or.jp

Taiki Ono***
taiki.ono@boj.or.jp

Akitoshi Toyoda****
akitoshi.toyoda@boj.or.jp

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Bank of Japan
2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo 103-0021, Japan

* Research and Statistics Department, Bank of Japan (currently Monetary Affairs Department)

** Graduate School of Economics, University of Tokyo

*** Research and Statistics Department, Bank of Japan

**** Research and Statistics Department, Bank of Japan (currently Financial System and Bank Examination Department)

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Ko Adachi† Kosuke Aoki‡ Yoshiyuki Kurachi§ Taiki Ono** Akitoshi Toyoda††

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Abstract

This study employs firm-to-firm transaction data to identify the multilayered and extensive supply chain structures in Japan's manufacturing sector and quantitatively analyze the characteristics of these supply chain structures. It also investigates the impacts of firm-level shocks, arising from both the supply and demand sides, on the overall manufacturing sector. The analysis reveals that automobile supply chains are exceptionally long and large-scale, with firms at the center of these chains exerting a larger influence on individual suppliers' production activities than in other industries. Furthermore, the findings indicate that supply constraints in products identified as potential bottlenecks can significantly dampen macroeconomic production. The results also highlight that holding inventory can serve as an effective measure to mitigate these impacts to a certain extent.

JEL Classification: C67, L14, L16
Keywords: Supply Chain, Firm-to-Firm Transaction Data, Network Centrality, Supply Constraints

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† Research and Statistics Department, Bank of Japan (currently Monetary Affairs Department) (kou.adachi@boj.or.jp)
‡ Graduate School of Economics, University of Tokyo (kaoki@e.u-tokyo.ac.jp)
§ Research and Statistics Department, Bank of Japan (yoshiyuki.kurachi@boj.or.jp)
** Research and Statistics Department, Bank of Japan (taiki.ono@boj.or.jp)
†† Research and Statistics Department, Bank of Japan (currently Financial System and Bank Examination Department) (akitoshi.toyoda@boj.or.jp)

1. Introduction

The multilayered and extensive supply chains of Japan's manufacturing sector are a defining feature of the nation's economic structure, and a feature which facilitates efficient value creation. On the other hand, during past business cycles, various external shocks—such as sudden declines in overseas demand or disruptions in the supply of materials—have propagated through these complex networks, flowing either downstream or upstream along the manufacturing process, ultimately generating negative dynamics in the macroeconomy[1].

Recent trade policies and geopolitical factors create aspects of both traditional macroeconomic shocks and idiosyncratic shocks that specifically impact certain firms or industries. Consequently, precisely capturing the structure, risks, and characteristics of Japan's manufacturing supply chains through high-granularity data has become increasingly important for evaluating the macroeconomic conditions and forecasting economic trends.

Motivated by these considerations, this paper integrates firm-to-firm transaction data with microdata on firms' manufactured products to examine the structural characteristics of supply chains in Japan's manufacturing sector. The paper can be summarized in the following three points:

First, we construct highly granular production network data at the firm-product level. Specifically, we use the Transaction Share Data from Teikoku Databank, which records inter-firm transaction information, the microdata on firms' manufactured products from the *Annual Business Survey* (hereafter ABS) conducted by the Ministry of Internal Affairs and Communications (MIC) and the Ministry of Economy, Trade and Industry (METI), and the input-output relationships documented in the *Input-Output Tables* compiled by the MIC. By integrating these three datasets, we estimate the flow of materials and components between firms. Consequently, we can identify the hierarchical structures of supply chains, with final goods manufacturers positioned at the top, and detect the products that could create supply chain bottlenecks.

Second, we identify the hierarchical structure of supply chains in Japan's manufacturing sector and quantitatively analyze its characteristics. Specifically, leveraging the highly granular production network data, we detect firms positioned at the top of the hierarchical supply chain—referred to as "focal firms[2]"—based on centrality measures, a

[1] Acemoglu et al. (2012) and Baqaee and Farhi (2019) theoretically show the mechanism by which idiosyncratic shocks cause fluctuations in the macroeconomy through production networks.

[2] Small and Medium Enterprise Agency (2020) refers to firms positioned at the very downstream end of inter-firm transaction networks as "focal firms (*choten kigyo* in Japanese)," and this paper adopts the same terminology.

standard concept in network theory. Furthermore, applying the Average Propagation Lengths (APL), a metric widely used in input-output analysis, we examine the hierarchical structure of suppliers linked to these focal firms. This approach enables us to systematically capture and visualize the key features of Japan's manufacturing supply chains.

Third, we identify products that could create supply chain bottlenecks and evaluate the potential impacts of supply constraints resulting from these products. Specifically, we identify products that are difficult to substitute and could significantly affect downstream production, based on centrality measures and market concentration levels. Additionally, we perform simulations to analyze the short-term impacts of supply constraints arise for the identified products.

(Literature Review)

This paper builds on three strands of prior research: the construction of high-granularity production network data; the identification of hierarchical structures within supply chains; and the evaluation of supply chain disruption risks.

For many years, the primary means of understanding a nation's production network was limited to input-output tables compiled by public institutions. Recently, however, as access to firm-level data maintained by public institutions has been opened up gradually, along with more disclosures from private companies, analyses using firm-level networks have become increasingly common (e.g., Barrot and Sauvagnat, 2016; Boehm et al., 2019; Dhyne et al., 2025; Bacilieri et al., 2026). In Japan, in particular, the availability of comprehensive inter-firm transaction network data collected by private credit research firms has driven the accumulation of pioneering empirical studies in this field (Saito et al., 2007; Ohnishi et al., 2009; Fujiwara and Aoyama, 2010; Mizuno et al., 2015; Bernard et al., 2019; Carvalho et al., 2021).

More recently, there have been attempts to further disaggregate firm-to-firm transaction networks. Specifically, an emerging body of literature constructs production networks that better reflect actual production processes by incorporating the input-output structure of products manufactured by each firm into firm-level transaction networks. For instance, Inoue and Todo (2024) estimate an establishment-product-level production network by combining inter-firm transaction data with establishment-level product data from the *Economic Census for Business Activity* (hereafter ECBS). Meanwhile, Mizuno et al. (2025) devise a method to construct a firm-product-level production network from firm-to-firm transaction data, identifying the input-output structure based on AI technologies. In addition, Katafuchi et al. (2025) estimate international transaction relationships at the firm and business-division level using corporate financial statements and customs records. The present paper is closest to the approach of Inoue and Todo (2024) as both studies use microdata from public statistics to convert inter-firm transaction data into a firm-product-level production network. However, whereas Inoue and Todo (2024) identify the input-output structure by assuming that an intermediate input is a product procured by more than half of the firms manufacturing the same product, this paper distinguishes itself by constructing a production network that more accurately reflects the actual economic structure through the integration of the input-output relationship derived from the *Input-Output Tables*.

Furthermore, based on network theory, research has progressed to unravel the complex firm-to-firm transactional relationships and understand their structural characteristics (Kim et al., 2011). In the field of identifying hierarchical structures within supply chains, multiple studies have applied techniques known as community detection, which are widely used in the analysis of Social Networking Services (SNS) and biological networks (Chakraborty et al., 2018; Wiedmer and Griffis, 2021; Lu and Dong, 2023). Unlike these studies, this paper applies the concept of centrality in network theory and the APL metric from input-output analysis to identify the hierarchical structure of manufacturing supply chains[3]. The unique aspect of this approach is its focus on a specific vertical structure in which suppliers are hierarchically connected to focal firms, which offers the advantage of straightforward interpretation of the identification results.

In recent years, the number of studies on supply chain disruption risks have also increased. In this field, Craighead et al. (2007) is recognized as one of the seminal works. Based on extensive survey data collected from firms, they identify three main factors that determine supply chain disruption risks: (1) density (the geographical clustering of suppliers); (2) complexity (the complexity of the supply chain); and (3) node criticality (the number of firms that could create bottlenecks). The bottleneck detection conducted in this paper is related to the third factor—node criticality.

The usefulness of centrality measures for detecting bottlenecks has been emphasized in various studies. Mizgier et al. (2013) identify three centrality measures—out-degree centrality, betweenness centrality, and radiality centrality—as indicators capable of capturing bottlenecks in supply chains. They argue that these measures have distinct characteristics and, therefore, should be applied depending on the specific analytical objectives. Yan et al. (2015) argue that betweenness centrality is suitable as an indicator for capturing the substitutability of supplier firms, based on their view that firms that frequently bridge between firms produce a significant proportion of the specific components supplied within the supply chain. While prior studies, including those mentioned above, have largely focused on conceptual discussions of these measures or analyses based on artificially generated networks, this paper is the first to apply

[3] Some studies analyzing transaction networks in payment systems identify the hierarchical structure using centrality measures, similar to our approach (Glowka et al., 2025; Okubo et al., 2026).

betweenness centrality to real-world firm-product-level production networks, successfully identifying firm-product pairs that could create bottlenecks.

Finally, there are also studies that attempt to evaluate the impact of supply chain disruptions using firm-level network data. Early research focused on analyzing supply chains within specific industries (Saavedra et al., 2008; Kito et al., 2014; Simchi-Levi et al., 2015). However, as data availability has improved, the scope of analysis has expanded to include cross-industry networks (e.g., Zhao et al., 2019; Inomata et al., 2026). Among these, studies focusing on Japan include Inoue and Todo (2019) and Inoue and Todo (2024). Inoue and Todo (2019) apply an Agent-Based Model, incorporating capital stock restoration and material inventories, to Japan's inter-firm transaction network to evaluate the impacts of natural disasters, such as the Great East Japan Earthquake. On the other hand, Inoue and Todo (2024) conduct simulations using a relatively simple model without inventory considerations but leverage highly detailed production networks at the establishment-product level. These studies align with the present paper in their focus on supply constraints at the product level and the role of inventories in mitigating these constraints. This study advances the literature by simultaneously incorporating both factors and performing simulations using actual firm-product-level inventory data.

The structure of the paper is as follows. Section 2 introduces the data used in the analysis and explains the methodology for constructing high-granularity production network data at the firm-product level. Section 3 visualizes Japan's manufacturing supply chains based on this production network data and examines their characteristics. Section 4 identifies products that could create supply chain bottlenecks and analyzes the impact of supply constraints for these products on Japan's manufacturing production. Section 5 concludes.

2. Construction of Production Network Data

2.1. Data

The firm-to-firm transaction data used in this study is Transaction Share Data provided by Teikoku Databank. This dataset includes not only the names of customers and suppliers but also their associated transaction shares[4], both collected by Teikoku Databank during

[4] The missing values in transaction shares are imputed using estimates from Teikoku Databank. For details on the estimation methodology, see Teikoku Databank (2022). In addition, note that there are two types of transaction shares: sales shares (the share of sales to each customer relative to the total sales of the firm) and procurement shares (the share of purchases from each supplier relative to the total purchase amount of the firm). In this paper, we use the sales share, which has higher coverage, as the transaction share. In the dataset, supplier-customer pairs with transaction shares below 0.01% are recorded with their transaction share

the credit investigation process. The availability of transaction shares enables us to capture the strength of inter-firm transactions in addition to their existence[5].

This paper analyzes a total of 105,481 domestic inter-firm transaction relationships among 15,022 manufacturing firms, each with a capital of at least 50 million yen, as of 2025. According to the *2024 Economic Census for Business Frame* (hereafter ECBF) conducted by the MIC, there are approximately 18,000 manufacturing firms with a capital of at least 50 million yen. This indicates that the firm-to-firm transaction data covers about 80% of these firms. Likewise, Table 1 presents the coverage of our sample in terms of financial and other attributes, demonstrating that the coverage for each financial attribute exceeds 70%.

(Table 1) Sample Coverage

	Number of firms	Number of employees	Sales	Labor costs	Investment
		(10 thous.)	(tril. yen)	(tril. yen)	(tril. yen)
Our Sample	*15,022*				
Manufacturing (Capital≥50 mil. yen)	17,737	562	391	30	15
[% of Total Manufacturing]	[9%]	[63%]	[84%]	[72%]	[89%]
Total Manufacturing	208,651	897	463	42	16

Note: The number of firms, the number of employees, and sales are based on the 2024 ECBF. Other figures are based on the 2021 ECBS. Investment includes tangible fixed assets (excluding land) and software.
Source: Ministry of Internal Affairs and Communications.

We link the transaction data to microdata from multiple official statistics using corporate numbers. Specifically, we obtain firm-product-level shipment values[6] from the ABS as well as firm-level sales from the *Basic Survey of Japanese Business Structure and Activities* (hereafter BSJBSA), both conducted by government ministries.

2.2. Methodology for Constructing Production Network Data

The aforementioned firm-to-firm transaction data encompasses all transactions among manufacturing firms, including those involving final-demand goods. Hence, to construct production network data that represents the input-output structure between firms, it is necessary to exclude transactions unrelated to intermediate inputs, such as purchases of

rounded down to 0%.

[5] Most other firm-to-firm transaction datasets record only the existence of transactions, with the transaction volumes or shares rarely being available. For this reason, many studies have attempted to estimate inter-firm transaction volumes (e.g., Inoue and Todo, 2019; Sato et al., 2026; Inomata et al., 2026).

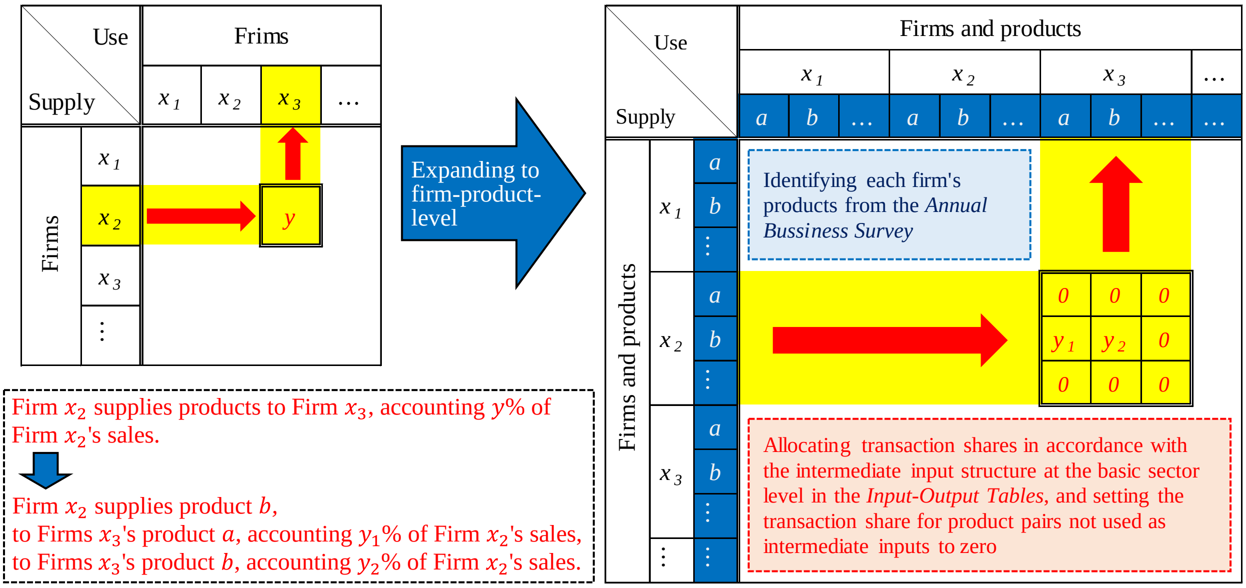
[6] As detailed later, the construction of a firm-product-level transaction network primarily uses data from the most recent survey, the 2024 ABS. However, in cases where data is missing for that particular year, we supplement it using earlier survey years (the 2022 or 2023 ABS) or the *2019 Census of Manufactures* and the *2020 Census of Manufactures*, which has broader coverage than the ABS.

capital goods for investment purposes.

In this paper, we address this issue by integrating inter-firm transaction data with firm-product-level shipment data obtained from the ABS and the input-output structure based on the basic sector classification of the *Input-Output Tables*.

Specifically, for each pair of firms with a transactional relationship, we obtain their products using the ABS and assess whether input relationships exist between these products based on the *Input-Output Tables*. We then distribute the transaction shares between firms across each product pair with an input relationship, thereby transforming the firm-level transaction data into firm-product-level production network[7]. Through this process, the transaction shares of product pairs without input relationships in the *Input-Output Tables*, such as the purchase of capital goods for investment purposes, are set to zero, enabling us to exclude transactions not related to intermediate inputs. When distributing the inter-firm transaction shares, it is assumed that the transaction shares of product pairs with input relationships are proportional to the sales shares of the products at the customer and supplier firms, as well as the input coefficients from the *Input-Output Tables* (Figure 1).

(Figure 1) Methodology for Constructing Production Network Data



Consequently, with transactions for final-demand purposes excluded, we constructed firm-product-level production network data that reflects the input-output structure of the manufacturing sector in a manner consistent with macro-level statistics. The resulting dataset comprises a total of 1,105,563 firm-product transactions involving 2,056 products among 13,013 firms.

[7] For details on the construction methodology, see Appendix 1.

3. Supply Chain Structure of Japan's Manufacturing Sector

In this section, using the production network data constructed above, we examine the supply chain structure of Japan's manufacturing sector and reveal its characteristics. Specifically, (i) we identify the supply chain structure, including the focal firms and their associated suppliers, and (ii) we quantify the length, scale, and impact propagation of each supply chain.

To simplify the analysis, the identification of focal firms and their suppliers is conducted at the firm level. Accordingly, in this section, the production network data is aggregated from the firm-product level to the firm level[8].

3.1. Identification of Supply Chains

(Focal Firms)

First, the identification of focal firms, which are located at the top of the supply chain, is conducted based on the conditions outlined in Table 2.

(Table 2) Criteria for Identifying Focal Firms

Supply Concentration: Authority centrality is greater than that of all customers.
Influence: The number of direct and indirect suppliers is large.
Intended Use of Products: The share of transactions with manufacturing customers is small.

The first criterion is supply concentration. Focal firms located at the downstream end of the supply chain are expected to receive supplies, directly or indirectly, from a large number of firms in the supply chain. This aspect is captured using authority-based eigenvector centrality (authority centrality, Bonacich, 1987). This metric evaluates the importance of each node (firm) in the network based on the number and strength of inward links (e.g., the number of transactions and the transaction shares) received from other nodes. As discussed later, firms with high authority centrality are receiving supplies, directly or indirectly, from many supplier firms. Thus, authority centrality tends to be high for firms located downstream in the supply chain[9].

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[8] Two potential issues may arise when using firm-product-level production network data. First, firms that produce both final products and components may simultaneously be identified as focal firms for their final products and as suppliers for their components. Second, for firms that produce multiple components, their positions within the supply chain may vary depending on the specific component. To address these issues, this paper aggregates the supply chain data to the firm level. The reaggregated version of firm-level network excludes transactions unrelated to intermediate inputs through the process described in Section 2.

[9] The counterpart to authority centrality is hub-based eigenvector centrality (hub centrality). This metric evaluates the importance of each node in the network based on the number and strength of outward links it directs to other nodes. Therefore, hub centrality tends to be high for firms located upstream in the supply

The firm-to-firm transaction network is represented by an adjacency matrix $\widetilde{W} = [\widetilde{w}_{i,j}]_{i,j=1,\dots,N_f}$. Here, each element $\widetilde{w}_{i,j}$ of the adjacency matrix $\widetilde{W}$ represents the proportion of firm i's sales to firm j, excluding non-intermediate transactions, relative to firm i's total sales. N_f denotes the total number of firms. Let $\alpha \in \mathbb{R}^{N_f}$ represent a vector whose elements correspond to the authority centrality of each firm. This centrality can be defined in a recursive manner using the adjacency matrix $\widetilde{W}$ as follows:

$$\alpha = \frac{1}{\rho(\widetilde{W}^T)} \widetilde{W}^T \alpha,$$

where $\rho(\widetilde{W}^T)$ represents the spectral radius[10] of transpose of adjacency matrix $\widetilde{W}$. Since the above equation can be transformed into $\widetilde{W}^T \alpha = \rho(\widetilde{W}^T)\alpha$, the authority centrality α is the eigenvector corresponding to the spectral radius of transpose of adjacency matrix $\widetilde{W}$.

Therefore, the authority centrality of firm i (i.e., α_i) is expressed as follows:

$$\alpha_i = \frac{1}{\rho(\widetilde{W}^T)} \sum_{j=1}^{N_f} \widetilde{w}_{j,i} \alpha_j,$$

where $\widetilde{w}_{j,i}$ represents the proportion of supplier j's sales to firm i relative to supplier j's total sales. Therefore, the authority centrality of firm i (i.e., α_i) becomes higher when firm i receives a large amount of intermediate goods from many suppliers. Moreover, due to its recursive structure, authority centrality incorporates not only the direct intermediate inputs but also the indirect intermediate inputs, as reflected through the authority centrality of the supplier j (i.e., α_j). Hence, authority centrality can be regarded as a metric that is closely associated with downstreamness in the supply chain.

These characteristics imply that if a customer has higher authority centrality than a given firm, it is unlikely that the firm is positioned at the very downstream end of the supply chain (i.e., it is not a focal firm). Therefore, under the first criterion, we require that a focal firm's authority centrality be greater than that of all its customers.

The second criterion is the magnitude of influence. For the purpose of identifying focal firms with a significant impact on the macroeconomy, we consider the number of firms that have direct or indirect input relationships within three transactional steps. Specifically, we require that a focal firm have input relationships, either direct or indirect, with at least 2,000 suppliers, placing it approximately in the top 10th percentile for this

chain.

[10] The spectral radius of a matrix refers to the largest absolute value among all the eigenvalues of the matrix.

measure[11].

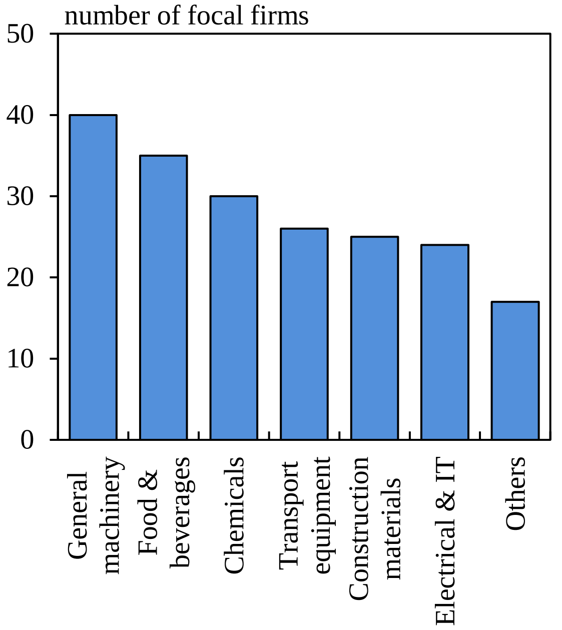
The third criterion is the intended use of products. Specifically, if the total transaction share within the manufacturing production network data constructed in the previous section is less than 5%, the firm is considered a producer of final-demand goods positioned at the very downstream end of the supply chain, which is a necessary condition for being a focal firm[12].

Under these conditions, a total of 197 focal firms were identified. As illustrated in Figure 2, many focal firms are producers of final-demand goods, including capital goods manufacturers classified under "General Machinery" (e.g., construction machinery, semiconductor manufacturing equipment, and machine tools) and "Electrical & IT" (e.g., communication equipment and electronic measuring instruments), as well as consumer goods manufacturers categorized under "Food and Beverages," "Transportation Equipment" (e.g., automobiles), and "Chemicals" (e.g., pharmaceuticals and cosmetics).

In fact, as shown in Figure 3, the final demand ratios of the primary products (i.e., products with the largest sales) of focal firms, calculated from the *Input-Output Tables*, are remarkably high. This result suggests that the identification criteria employed in this section effectively capture focal firms positioned at the downstream end of the supply chain. It is worth noting, however, that the inclusion of some firms with low final demand ratios among the focal firms may be attributable to factors such as (i) disconnections in the network data when transactions go through wholesalers[13], and (ii) the coarse classification used in the *Input-Output Tables*[14].

[11] Since additional conditions are imposed in identifying tier firms, as described later in this paper, the number of tier firms associated with each focal firm does not necessarily exceed 2,000.
[12] A sales share of less than 5% within the production network data of this study suggests that these firms primarily have either a high sales share to non-manufacturing firms or a large volume of sales to other manufacturing firms for purposes other than intermediate transactions.
[13] For example, products such as steel products classified under "Construction Materials" are often traded through trading companies.
[14] For example, printed products classified under "Others" include both items such as packaging paper, which serves as an intermediate input in manufacturing (and thus has a low final demand ratio), and items such as newspapers, which are not used as intermediate inputs in manufacturing (and thus have a high final demand ratio). However, the *Input-Output Tables* group both under the same product category.

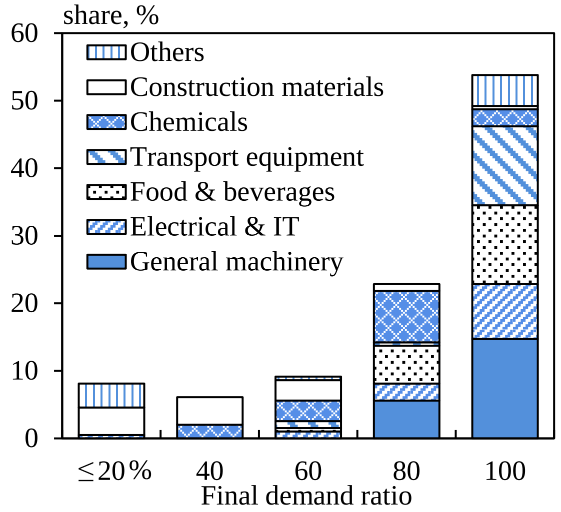
(Figure 2) Number of Focal Firms by Industry



Note: General machinery: General-purpose, production, and business-oriented machinery; Electrical & IT: Electrical machinery, information and communication machinery, and electronic components/devices; Chemicals: Chemicals and plastic products; Construction materials: Iron and steel, non-ferrous metals, metal products, ceramic, stone and clay products, wood and wood products, furniture, and petroleum and coal products; Others: Textiles, pulp/paper, printing, rubber products, leather products, and other manufacturing.

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

(Figure 3) Final Demand Ratio of Focal Firms



Note: The "Final demand ratio" represents the value of the basic sector classification in the *Input-Output Tables* to which the product with the largest shipment value for each focal firm belongs. It is calculated as: Final demand / (Intermediate demand of manufacturing + Final demand).

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

(Supplier Firms)

Next, for each focal firm detected above, we identify the supplier firms within its supply chain, along with their positions in the supply chain (i.e., tiers). In this paper, we refer to supplier firms with defined tiers as "tier firms."

For the identification of tier firms, we employ the Average Propagation Lengths (APL) proposed by Dietzenbacher et al. (2005), a metric widely used in input-output table analysis. The APL is an index that represents the average number of stages required for production inducement originating from a specific industry to reach other industries, thereby measuring the distance between industries based on the input-output structure. When this metric is applied to the inter-firm network $\widetilde{W}$ in this study, the APL ($APL_{i,j}$) between firm i and firm j is calculated based on the following equation:

$$APL_{i,j} = \sum_{k=1}^{\infty} k\left(\left[\widetilde{W}^{k}\right]_{i,j} \Big/ \sum_{k=1}^{\infty}\left[\widetilde{W}^{k}\right]_{i,j}\right),$$

where k denotes the transaction count, and the coefficient within the parentheses following k serves as its weight. This weight indicates the proportion of the total transaction value—both direct and indirect—that is generated by the k-th transaction. Accordingly, the APL can be interpreted as a metric showing the average number of transactions required to connect two firms within the network.

Therefore, by using the APL, it becomes possible to uniquely determine the distance between a supplier and a focal firm, even when multiple transactional paths exit between them. Based on the calculated APL, the tier of each firm is identified according to the conditions outlined in Table 3.

(Table 3) Criteria for Identifying Tier Firms

- Calculate the APL of each firm with respect to each focal firm. Based on the calculated APL values, assign tiers as follows.

$$Tier1 : 1 \leq APL < 1.5$$
$$Tier2 : 1.5 \leq APL < 2.5$$
$$Tier3 : 2.5 \leq APL < 3.5$$

… (the same applies below)

- It is permitted for a firm to be a tier firm for multiple focal firms.

Firms are excluded from being classified as tier firms if they fail to meet the following conditions, as they are considered to lack economically significant connections within the supply chain. First, firms with weak connections to the focal firm (i.e., where the total of direct and indirect transaction share is less than 0.01%) are not included as tier firms[15]. Second, firms without direct or indirect connections to the focal firm's primary product in the firm-product-level production network data constructed in the previous section, are also excluded[16].

The number of tier firms identified for the 197 focal firms is as follows: Tier 1: 6,352 firms, Tier 2: 50,283 firms, Tier 3: 39,710 firms, Tier 4: 9,366 firms, Tier 5: 519 firms, and Tier 6: 2 firms. First, we analyze the characteristics of these tier firms based on financial and other attributes (Table 4). Focal firms are found to be significantly larger in terms of capital, sales, and number of employees. Among the tier firms, those positioned closer to

[15] As described in Section 2.1, the Transaction Share Data records transaction shares by truncating those below 0.01% to 0%. Therefore, we use this value (0.01%) as the threshold for evaluating the strength of inter-firm connections.
[16] Since we use the production network data reaggregated at the firm level to calculate the APL, this condition is additionally imposed.

the downstream stages of the supply chain, such as Tier 1 and Tier 2 firms, tend to exhibit larger sales. This reflects the nature of supply chains, where value is added by assembling and processing intermediate goods procured from suppliers. Additionally, both capital investment and the number of employees are observed to be larger for downstream firms, particularly those in Tier 1 and Tier 2. This suggests a structural tendency where production equipment and labor inputs are larger on average in downstream firms. It is also worth noting that some large material manufacturers are classified into relatively downstream tiers, such as Tier 1 or Tier 2, due to their direct transactional relationships with focal firms.

(Table 4) Financial and Other Attributes of Focal Firms and Tier Firms

		Capital (100 mil. yen)	Sales (100 mil. yen)	Investment (100 mil. yen)	Number of employees	Number of firms
Focal firms		20.0	536.1	15.5	990	197
Tier firms	1	3.0	129.2	3.4	339	6,352
	2	1.0	60.6	1.5	189	50,283
	3	1.0	47.5	1.2	155	39,710
	4	1.0	44.3	1.2	139	9,366
	5	0.9	34.0	1.0	119	519

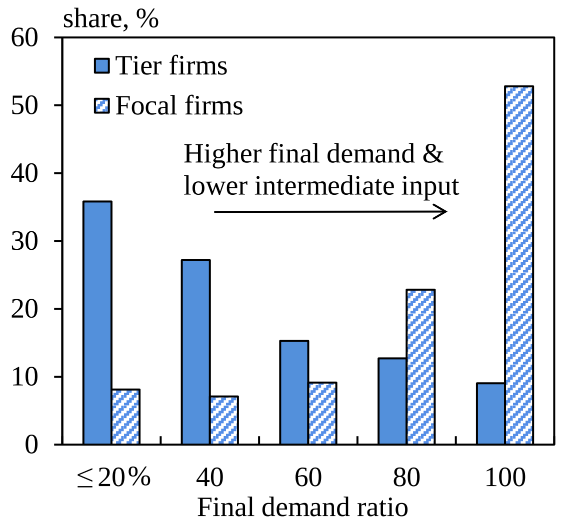
Note: The medians of financial and other attributes for each classification are calculated from the microdata of BSJBSA. In principle, the values are as of fiscal 2023.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

Figure 4 presents the final demand ratios for these tier firms, akin to the analysis of focal firms shown in Figure 3. The final demand ratios of tier firms are clearly lower compared to those of focal firms. This result indicates that the supply chain identification method proposed in this paper, as outlined in Table 2 and Table 3, effectively distinguishes between final goods producers and intermediate goods producers.

Next, Figure 5 presents the number of tier firms identified for each of the 197 focal firms, sorted in descending order by industry. In the supply chains of "Transport equipment," including automobile manufacturers, there are, on average, nearly 2,000 tier firms, making their supply chain scale notably larger than that of other industries. Similarly, in "General machinery," particularly among construction machinery manufacturers, supply chains with approximately 3,000 to 4,000 tier firms can be observed.

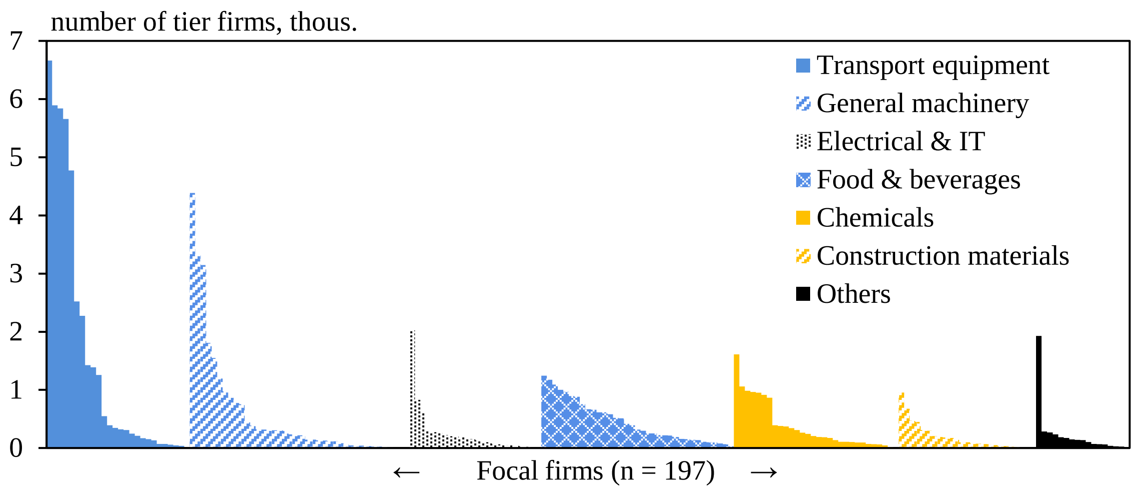
In contrast, the supply chains of "Electrical & IT," while some may be substantially large, tend to have a relatively smaller average scale compared to "Transport equipment" and "General machinery." This contrast reflects the distinct characteristics of these industries: "Transport equipment" is marked by vertically integrated corporate relationships (commonly referred to as *keiretsu*) within Japan, whereas "Electrical & IT" has experienced the advancement of horizontal integration on a global scale. Although supply chains in non-durable goods industries such as "Food and beverages" are typically domestically constructed, they are relatively smaller in scale compared to those in machinery-related industries, reflecting fewer processing stages.

(Figure 4) Final Demand Ratio of Tier Firms



Note: The final demand ratio of tier firms is calculated for each pair of a tier firm and a forcal firm. It refers to the value of the basic sector classification in the *Input-Output Tables*, associated with the product of the tier firm that is most supplied to the focal firm's main product. The final demand ratio of focal firms is identical to that in Figure 3.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

(Figure 5) Number of Tier Firms by Focal Firm



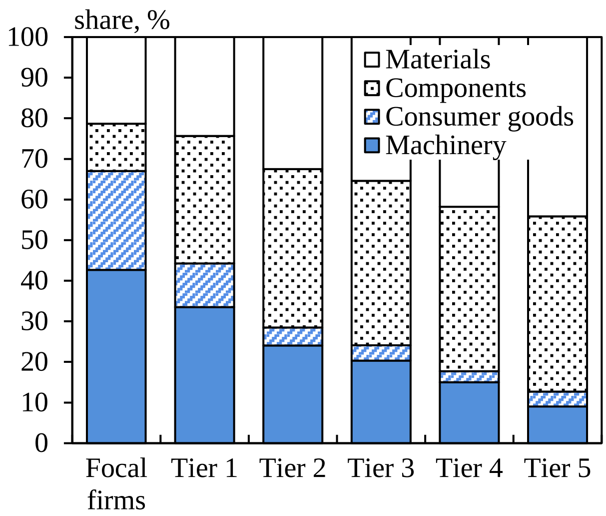
Note: For each industry of focal firms, the number of tier firms belonging to the supply chain of each focal firm is displayed in descending order.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

Finally, let us examine the characteristics of the identified tier firms by their respective tiers. Figure 6 categorizes the firms within each tier by industry[17]. It demonstrates that as we move from Tier 1 to Tier 5, the proportion of industries associated with "Components" (such as plastics, metal products, electronic components, and devices) and "Materials"

[17] As the number of Tier 6 firms is small, they are not shown in Figures 6 and 7.

(such as chemicals, steel/non-ferrous metals, ceramics, and stone products) increases noticeably. This observation confirms that the identified tiers effectively reflect the production stages within the supply chain.

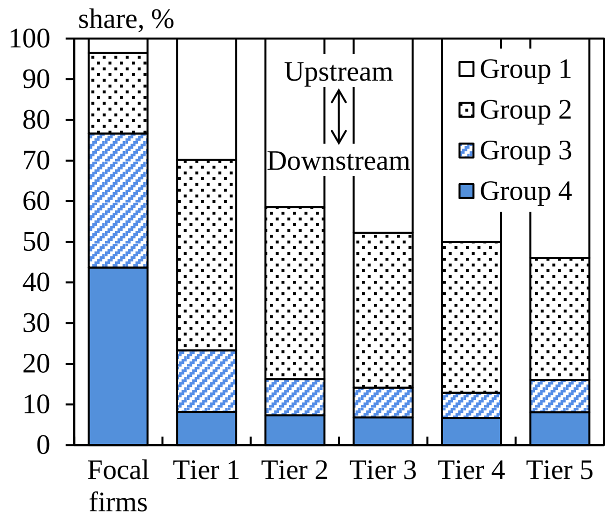
(Figure 6) Industry Composition



Note: Classification is based on the industry of the product most supplied by each tier firm to the main product of its focal firm. Materials: Steel, non-ferrous metals, chemicals, petroleum and coal, ceramics, stone, and clay, rubber, paper and pulp, textiles, wood and wood products. Components: Plastics; metal products, electronic components and devices, and printing. Consumer goods: Food and beverages, furniture, leather, and other manufacturing. Machinery: General-purpose, production, and business-use machinery, electrical machinery, information and communication equipment, transport equipment.

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

(Figure 7) Upstreamness and Downstreamness



Note: Classification is based on the relative upstreamness of the basic sector classification in the *Input-Output Tables* to which the product most supplied by each tier firm to the main product of its focal firm belongs. The relative upstreamness (upstreamness / (upstreamness + downstreamness)) is calculated from the input-output structure at the basic sector classification level of the *Input-Output Tables* (limited to the manufacturing sector) and grouped into quartiles.

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

This point is further analyzed using upstreamness and downstreamness indicators[18], which are widely used in the context of global supply chains (Antras et al., 2012; Miller and Temurshoev, 2017). Specifically, we calculate the upstreamness and downstreamness for each sector using the finest level of classification available in the input-output tables, thereby quantifying the relative position of each sector within the supply chain as "relative upstreamness." Based on this indicator, industries are divided into four quartiles, and both focal firms and tier firms are classified into these four groups (Figure 7). Group 1 represents the most upstream position in the supply chain, while Group 4 represents the

[18] Upstreamness refers to "the average number of production stages required for an industry's output to reach final consumers," while downstreamness refers to "the average number of production stages required for primary factor inputs to be incorporated into that industry's production." Furthermore, the sum of upstreamness and downstreamness can be interpreted as the total length of the supply chain associated with each industry. By combining these two indicators, it is possible to quantitatively evaluate the relative position of each industry within the global value chain.

most downstream position. As shown in Figure 7, moving from Tier 1 to Tier 5, there is a clear increase in the proportion of firms in Groups 1 and 2, which correspond to the upstream end of the supply chain. These results indicate that the tiers identified in this study effectively represent the hierarchical structure of the supply chain.

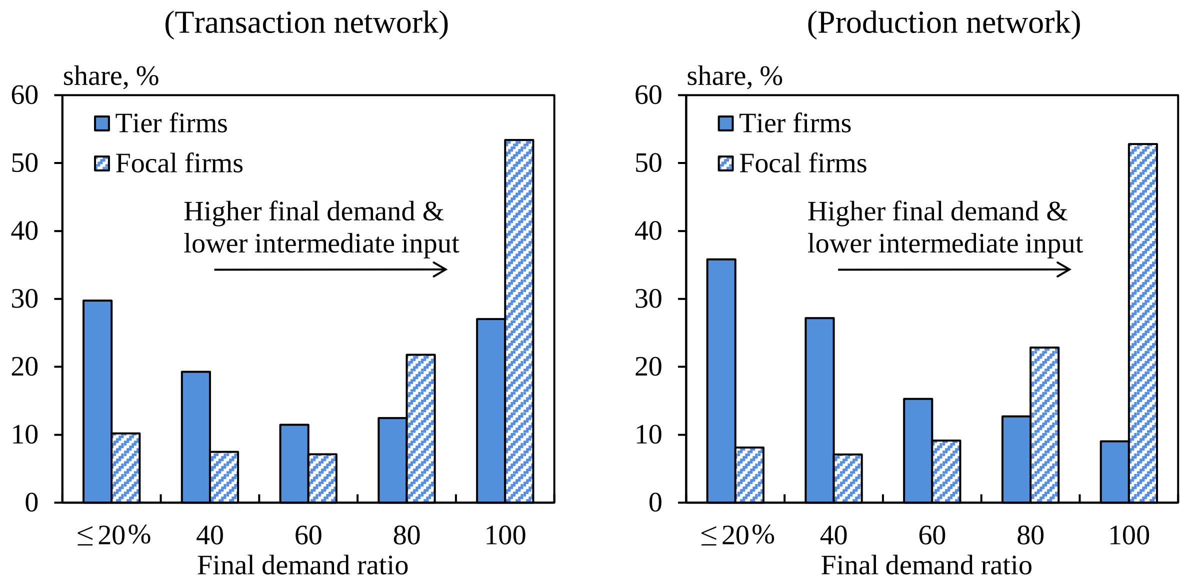
(Comparison with Identification based on Transaction Data)

At the end of this subsection, we compare the supply chain identification results based on the production network data constructed in this paper with the results obtained using the original firm-level transaction data.

We use the original firm-level transaction data instead of the reaggregated firm-level production network data to identify focal and tier firms under the conditions specified in Tables 2 and 3. Then, we calculate the final demand ratios for their major products. Figure 8 shows that while firms with high final demand ratios were correctly identified as focal firms when using the transaction data, a significant number of these firms were also incorrectly identified as tier firms. This confirms that final goods producers and intermediate goods producers were not distinguished properly.

These results indicate that converting the firm-level data to the firm-product-level, removing transactions unrelated to intermediate inputs (e.g., the capital goods purchase), and constructing the reaggregated firm-level production network makes it possible to identify the supply chain structure more accurately than when using the original firm-level transaction network.

(Figure 8) Final Demand Ratio of Focal Firms and Tier Firms



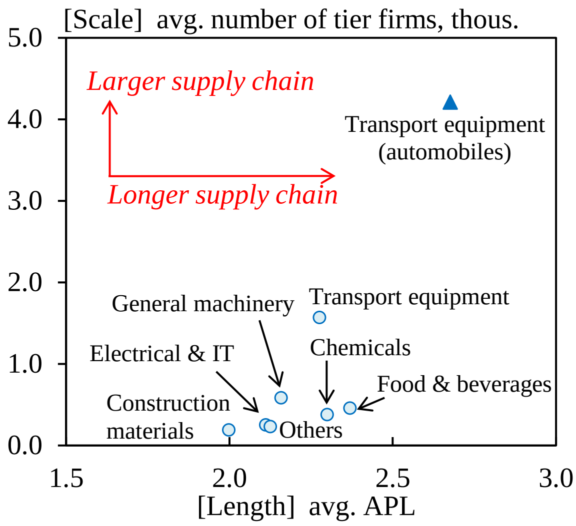
Note: The "Final demand ratio" represents the value of the basic sector classification in the *Input-Output Tables* to which the product with the largest shipment value for each firm belongs. It is calculated as: Final demand / (Intermediate demand of manufacturing + Final demand). The right panel is from Figure 4.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

3.2. Characteristics of Supply Chains

In this subsection, we examine the characteristics of the supply chains identified in the previous subsection from the perspectives of (1) length, (2) scale, and (3) impact propagation.

Figure 9 shows the average APL of tier firms within each supply chain and the average number of tier firms per focal firm, both calculated for the industries to which the focal firms belong. The average APL represents the length of the supply chain, while the average number of tier firms reflects the scale of the supply chain. As illustrated in Figure 9, the "Transport equipment" industry, particularly "Automobiles," is notable for having significantly longer and larger supply chains.

(Figure 9) Length and Scale of Supply Chains by Industry of Focal Firms



Note: The vertical axis represents the average of the number of tier firms for each focal firm by industry. The horizontal axis represents the average of the APL of tier firms for each focal firm by industry.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

This implies that demand fluctuations experienced by automobile manufacturers can influence the production activities of a wide range of tier firms. To explore further, we compare focal firms based on the magnitude of their impact on the production activities of individual tier firms. Specifically, we compute the relative exposure ($\psi(i,j)$) of each tier firm to the demand fluctuations faced by each focal firm, as defined by the following equation:

$$\psi(i,j) = \frac{l_{i,j} \times y_j}{\sum_{j \in T_i} l_{i,j} \times y_j},$$

where i represents tier firm i, and j represents focal firm j, and T_i is the set of focal firms to which tier firm i belongs. Additionally, $l_{i,j}$ is the (i,j)-th component of the Leontief inverse matrix[19], and y_j represents the sales of focal firm j. Within the framework of input-output analysis, the (i,j)-th element of the Leontief inverse matrix represents the increase in the gross output of firm i resulting from a one-unit increase in final demand for firm j. Therefore, the numerator of $\psi(i,j)$ captures the impact on the gross output of tier firm i when the demand for focal firm j fluctuates by a given percentage (x%). The value of $\psi(i,j)$ standardizes this impact into a relative measure. Specifically, a larger value of $\psi(i,j)$ indicates that tier firm i is more heavily affected by demand shocks originating from that specific focal firm.

Furthermore, by aggregating $\psi(i,j)$ as outlined in the following equation based on the industry of focal firm j, we compare the magnitude of the impact that demand fluctuations experienced by focal firms have on the production activities of individual tier firms across different focal firms' industries.

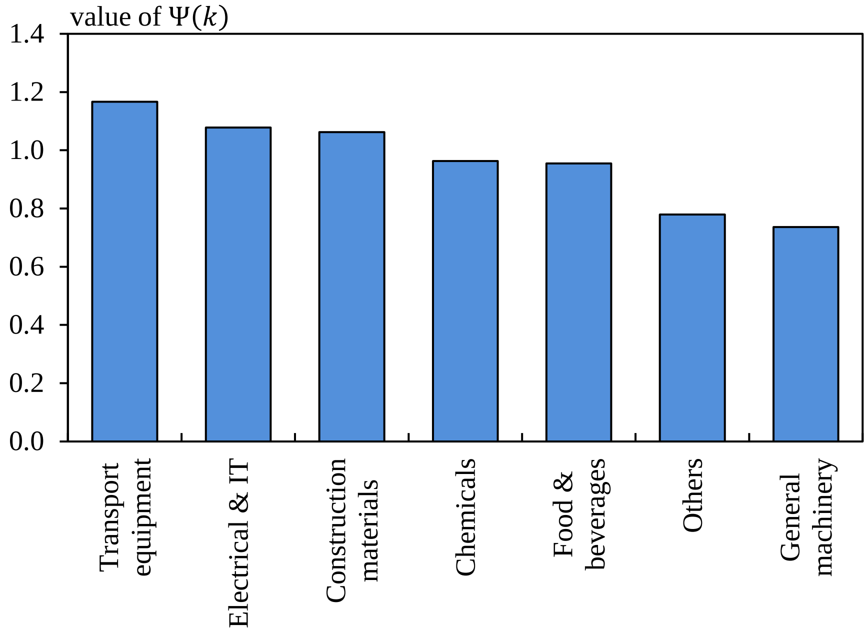
$$\Psi(k) = \frac{\sum_{i \in J} \sum_{j \in T^k} \psi(i,j)}{\sum_{i \in J} \sum_{j \in T^k \cap T_i} 1/|T_i|}$$

Here, J represents the entire set of sample firms, T^k denotes the set of focal firms belonging to industry k, and $|T_i|$ indicates the number of focal firms to which tier firm i is connected. The numerator is the sum of $\psi(i,j)$ across all focal firms in industry k, while the denominator serves as a normalization factor. Specifically, $\psi(i,j) = 1/|T_i|$ $(\forall j \in T_i)$ holds when tier firm i has equal exposure to each of its focal firms. Consequently, $\Psi(k)$ exceeds 1 if the exposure of tier firms to the focal firms in industry k is, on average, higher than this baseline level.

Figure 10 shows the calculation results of $\Psi(k)$. As indicated in this figure, focal firms in the transport equipment industry, including automobiles, not only have an exceptionally large number of tier firms, as observed in Figure 10, but also have a larger impact on the production activities of individual tier firms than other focal firms.

[19] The input coefficient matrix used to calculate the Leontief inverse matrix was constructed by transforming a firm-level output coefficient matrix. This transformation uses sales data from the BSJBSA (or total shipment values from the ABS for firms outside the sample of the former survey).

(Figure 10) Impact Indicator of Focal Firms on Tier Firms' Production (by Industry)



Note: The figure shows the value of $\Psi(k)$ calculated by industry of focal firms.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

As shown by the preceding analysis, quantitative findings confirm that within the supply chains of Japan's manufacturing industry, the transport equipment sector—particularly automobile manufacturers—stands out with remarkable characteristics in terms of length, scale, and impact propagation. While the length and scale of these supply chains have previously been noted qualitatively, the use of actual inter-firm transaction data has now provided a quantitative perspective on these features.

3.3. Limitations

At the end of this section, we note two caveats regarding the analysis presented.

First, the quality of the firm-product-level production network data in this paper depends on the granularity and constraints of the underlying data. While the 6-digit level of product classification used in the ABS is highly granular, products within the same category are subdivided further based on specifications in reality. In addition, when combining firm-to-firm transaction data with firm-level data on manufactured products to estimate firm-product-level transactions, average input relationships between products are assumed, as described in the *Input-Output Tables*. Consequently, errors may remain in the estimated firm-product-level transactions.

Second, this paper does not incorporate transactions involving non-manufacturing industries, such as wholesalers, nor international transactions. Therefore, attention must be paid to the impact of these omissions on identifying supply chain structures. Since the network disconnects when transactions pass through wholesale trading companies or overseas, the connectivity and length of supply chains may be underestimated in industries where wholesale trading companies play a critical role, as well as in industries such as electronics and IT, where global supply chains have evolved significantly and production processes extend not only domestically but also overseas.

4. Supply Chain Bottlenecks

Such supply chain structures are a defining feature of Japanese economy, enabling efficient value creation. However, they also present vulnerabilities, as they can amplify and propagate economic shocks when disruptions occur at any point in the network. Indeed, Japan has repeatedly experienced cascading supply constraints. These have been triggered not only by macroeconomic shocks—such as the Great East Japan Earthquake and the COVID-19 pandemic—but also by idiosyncratic shocks, including localized component shortages caused by accidents at individual firms.

Therefore, in this section, we identify products that could have a significant impact on overall supply chain production in the event of supply constraints, referring to them as "bottleneck products," and assess their potential impacts.

4.1. Identification of Bottleneck Products

In long and complex supply chains, various types of bottlenecks can arise. For instance, supply constraints on raw materials at the very upstream of the supply chain are almost certain to impact the production activities of numerous firms. However, to fully understand the supply-side risks inherent in the economy, it is particularly important to identify intermediate goods that are difficult to substitute, while not always recognized as major risks due to their midstream position in the supply chain. With this objective in mind, this study uses the firm-product-level production network constructed in Section 2 to identify bottleneck products, defined as the manufacturing products of specific firms that meet the criteria outlined in Table 5[20,21].

[20] In addition to these criteria, firms and products with weak connections to the primary manufacturing products of focal firms (defined as having a direct or indirect transaction share of less than 0.01%) are also excluded from the list of potential bottlenecks.

[21] For each condition, this paper uses quartile points as thresholds. However, we confirmed that the results of the analysis presented in this section remain qualitatively unchanged when the thresholds are adjusted within a reasonable range.

(Table 5) Criteria for Identifying Bottleneck Products

Key Position: High betweenness centrality
Low Substitutability (I): High market share
Low Substitutability (II): High heterogeneity

The first criterion for identifying bottleneck products is the extent to which a node serves as a critical link within the supply chain. To evaluate whether the supply disruption of a specific firm's product could significantly constrain downstream production activities, hub-based centrality—which measures the number of downstream recipients—is considered a good indicator. However, because this metric is strongly associated with upstreamness in the supply chain, it is less suited to identifying the bottleneck products targeted in this study. Instead, "betweenness centrality" (Freeman, 1977) is considered a more appropriate metric, as it not only accounts for the number of downstream recipients, but also captures the intermediary role of a node within the supply chain. The utility of betweenness centrality has also been highlighted in previous studies on methods for detecting bottlenecks (Mizgier et al., 2013; Yan et al., 2015).

Specifically, the betweenness centrality $b(v)$ of a product v produced by a certain firm is defined as follows:

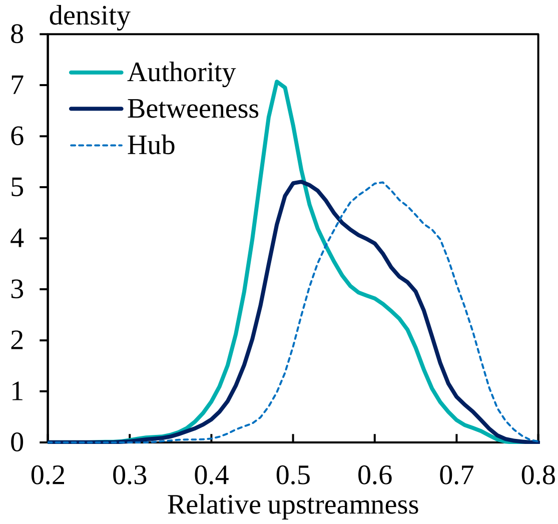
$$b(v) = \sum_{x,y \in V \setminus \{v\}} \frac{|S(x,v,y)|}{|S(x,y)|},$$

where V denotes the entire set of firm-product pairs, $|S(x,y)|$ represents the total number of shortest paths[22] between firm-product x and firm-product y, and $|S(x,v,y)|$ indicates the number of shortest paths between x and y that pass through firm-product v. Consequently, firm-product pairs with high betweenness centrality frequently occur on the shortest paths linking upstream and downstream entities and can be interpreted as key nodes within the supply chain. As Mizgier et al. (2013) observe, unlike hub-based centrality, betweenness centrality tends to be higher at intermediate points in the supply chain rather than at upstream positions, making it well-suited to the objectives of this study. Using the production network data in this study[23], Figure 11 illustrates the relationship between various centrality measures and supply chain positions (relative upstreamness). The results indicate that hub centrality is positively correlated with upstreamness, authority centrality is associated with greater downstreamness, and betweenness centrality tends to peak at

[22] The shortest path is defined as the path with the minimum number of edges between the starting point and the endpoint.
[23] Both centrality measures and relative upstreamness, in Figure 11, are calculated using production network data reaggregated at the firm level due mainly to the high computational load.

intermediate positions. Based on this, the first criterion for identifying bottleneck products in this study is that their betweenness centrality must rank within the top 25% of the distribution.

(Figure 11) Upstreamness of Top 25% Firms by Each Centrality Measure



Note: The figure shows the distribution of relative upstreamness among firms in the top 25% for each centrality measure. The density is based on kernel density estimation. Relative upstreamness is calculated as upstreamness / (upstreamness + downstreamness). Both centrality and relative upstreamness are calculated using production network data reaggregated at the firm level.

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

The second and third criteria focus on the low substitutability of a product, which is a critical characteristic of a bottleneck. Two separate measures are used to evaluate this aspect. The first measure is the degree of market concentration. Products for which supply capacity is highly concentrated in certain firms are generally difficult to substitute, especially in the short term, if supply constraints occur at those firms. To reflect this consideration, the second criterion requires that a firm's shipment share of the relevant product be 25% or greater.

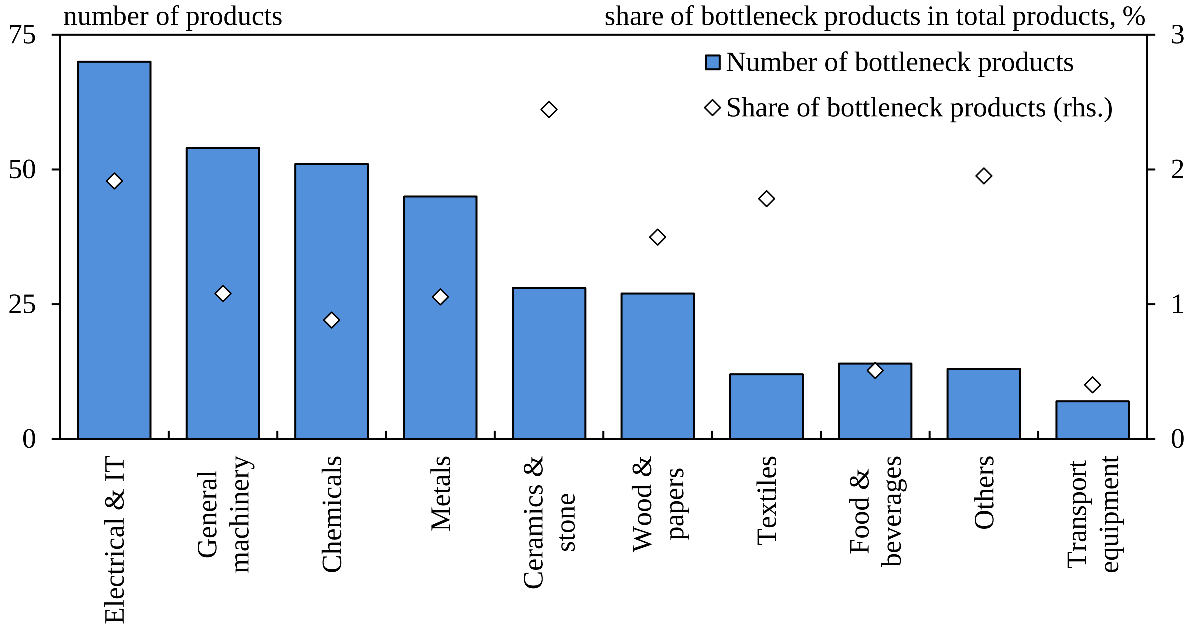
Another measure of substitutability is the degree of heterogeneity among goods, as indicated by variation in product prices. Products that are more homogeneous are generally considered easier to substitute, including from import substitutes, even if a particular firm faces a supply constraint. In this study, variations in shipment prices are utilized as a proxy for measuring product homogeneity[24]. Typically, products that are more homogeneous tend to have smaller variations in shipment prices, assuming other factors remain constant. Consequently, products with shipment price variations—measured by the coefficient of variation—that rank within the top 25% are classified as highly heterogeneous and

[24] The shipment price for each product was calculated using microdata from the 2024 ABS by dividing the shipment value by the shipment volume. However, it is worth noting that for highly customized products, where defining shipment volume is difficult and such data is not provided, these products were classified as highly heterogeneous.

technically difficult to substitute, forming the basis for the third criterion.

Under these conditions, a total of 321 bottleneck products, manufactured by 286 firms, were identified. As shown in Figure 12, the distribution of these bottleneck products is concentrated in industries such as "Electrical & IT," "General machinery," "Chemicals," and "Metals." These sectors encompass not only automotive-related products but also many materials and components used in the production of semiconductors and electronic parts, such as integrated circuits (Electrical & IT) and piston rings (General machinery).

(Figure 12) Number of Bottleneck Products by Industry



Note: The number of bottleneck products represents the industry distribution of 312 firm-product pairs identified as bottleneck products. The share of bottleneck products in total products indicates the ratio of the number of bottleneck products to the total number of firm-product pairs in each industry contained in the production network data. Electrical & IT: Electrical machinery, information and communication machinery, electronic components and devices. General machinery: General-purpose, production, and business-use machinery. Chemicals: Chemicals, plastics, petroleum and coal, and rubber. Metals: Steel, non-ferrous metals, and metal products. Wood & paper: Wood and wood products, paper and pulp, and printing. Textiles: Textiles and leather.

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

In terms of the proportion of bottleneck products relative to the total number of products in each sector, a significant number of products in the "Electrical & IT" sector have been identified as bottlenecks. This is likely because this sector includes a numerous number of widely used components, such as semiconductors and electronic parts, which are utilized in various industries. In contrast, bottleneck products in the "Chemicals" sector are relatively fewer compared to their overall product distribution. This can likely be attributed to the identification criteria, which take into account factors such as betweenness centrality and product heterogeneity, thus excluding products with high upstream involvement or those that are closer to commodities. Furthermore, intermediate goods within sectors like "Food & beverages" and "Transportation equipment" tend to be identified less frequently as bottleneck products due to the narrower range of industries in which they are applied.

4.2. Simulation of the Propagation of Supply Constraints in Bottleneck Products

Next, we will conduct a simulation to analyze the propagation effects of supply constraints in these bottleneck products[25]. This section begins by explaining the construction and solution methodology of the model, followed by presenting the simulation results derived from the model and discussing the impacts of supply constraints on production.

The analytical framework of this paper bears similarities to that of Inoue and Todo (2019) in that it assumes a Leontief-type production function for each firm and accounts for material inventories. However, whereas Inoue and Todo (2019) focused on analyzing the impacts of natural disasters and incorporated the damage and recovery of capital stock, these aspects are not considered in this study. Instead, this paper allows for a more detailed and granular analysis by utilizing the firm-product-level network constructed in Section 2[26].

(Model Construction)

First, we outline the framework of the model used for the simulation, differentiating between cases with and without inventories.

(1) The Case without Inventories

Let the production of product a by firm i be denoted as $y_{(i,a)}$, and let the production level under normal circumstances without supply constraints be $\bar{y}_{(i,a)}$. Moreover, their ratio is expressed as $\hat{y}_{(i,a)} = y_{(i,a)}/\bar{y}_{(i,a)}$. Assuming there are no inventories, $\hat{y}_{(i,a)}$ is determined as follows:

$$\hat{y}_{(i,a)} = \min\left\{\sum_{j\in J} \bar{\omega}_{(j,b)\to(i,a)}\hat{y}_{(j,b)}\right\}_{b\in B(i,a)}, \tag{1}$$

[25] In this study, bottleneck products are identified based on domestic production network data. Accordingly, in the subsequent simulations, the initial shock is assumed to stem from a reduction in domestic production, irrespective of whether the supply constraint originates from domestic or international factors. Given that Japan has traditionally been a resource-importing nation and its manufacturing sector operates within a complex and highly integrated global supply chain, it may also be worth explicitly isolating imported goods as the source of supply constraints. To address this perspective, Appendix 2 examines an extension of the model to incorporate supply constraints on imported goods.

[26] Inoue and Todo (2024) also utilize establishment-product-level granular data, but employ a simpler model than Inoue and Todo (2019) and this paper.

where J represents the entire set of sample firms, and $B(i,a)$ denotes the set of products that firm i uses as inputs to produce product a. Additionally, $\overline{\omega}_{(j,b)\to(i,a)}$ represents the extent to which firm i depends on supplier firm j for the procurement of intermediate product b when producing product a under normal circumstances. In other words, it denotes the procurement ratio of intermediate product b from supplier firm j and is defined as follows:

$$\overline{\omega}_{(j,b)\to(i,a)} = \frac{\bar{x}_{(j,b)\to(i,a)}}{\sum_{j\in J}\bar{x}_{(j,b)\to(i,a)}}, \qquad (2)$$

where $\bar{x}_{(j,b)\to(i,a)}$ represents the amount of product b produced by supplier j that is used by firm i to produce product a under normal circumstances. Since summing $\overline{\omega}_{(j,b)\to(i,a)}$ over the entire set of sample firms J equals 1, it is implicitly assumed that there are no procurements from outside the sample firms, such as imports or purchases from trading companies.

What Equation (1) suggests is the assumption of a Leontief-type production function, which implies complete non-substitutability among input product categories. As a result, the production of product a by firm i is constrained by the intermediate good in $B(i,a)$ that faces the largest reduction rate. This assumption is adopted to evaluate the impacts of supply constraints in the short term, where substitution between products is considered difficult.

Additionally, Equation (1) assumes that the input of each intermediate good is determined as a weighted average of the production of each supplier ($\hat{y}_{(j,b)}$), indicating a linear functional form within the same product category. However, even with a linear production function, it is assumed that substitution with alternative suppliers is not feasible. This means that any reduction in procurement from a constrained supplier directly results in a decrease in the input amount of that product. These assumptions are consistent with the our definition of bottleneck products, which are characterized by the difficulty of securing alternative procurement even within the same product category[27].

(2) The Case with Inventories

Next, we introduce the model that incorporates inventories. In this framework, we consider two types of inventories: product inventories and material inventories. Let $s^p_{(i,a)}$ represent

[27] The same assumptions are applied to inputs other than bottleneck products. However, in this simulation, the products facing supply constraints are all those that directly or indirectly depend on heterogeneous bottleneck products as inputs. Consequently, it is considered reasonable to assume that these products also possess a relatively high degree of heterogeneity and that difficulties are encountered in securing alternative procurement in the short run.

the product inventory of product a produced by firm i, and let $s^m_{b\to(i,a)}$ represent the material inventory of intermediate good b used by firm i in the production of product a. These inventories are expressed as ratios relative to the normal production levels and material input amounts: $\hat{s}^p_{(i,a)} = s^p_{(i,a)}/\bar{y}_{(i,a)}$ and $\hat{s}^m_{b\to(i,a)} = s^m_{b\to(i,a)}/\bar{x}_{b\to(i,a)}$. For instance, if $\bar{y}_{(i,a)}$ represents the annual production level under normal conditions, $\hat{s}^p_{(i,a)}$ indicates the equivalent number of years' worth of product inventory available at the normal production rate (the same applies similarly to $\hat{s}^m_{b\to(i,a)}$).

Incorporating inventories allows shipments to be supplemented from product inventories, even when production level declines. Similar to the production case, let $q_{(i,a)}$ denote the shipment value of product a by firm i, $\bar{q}_{(i,a)}$ the shipment value under normal circumstances, and their ratio expressed as $\hat{q}_{(i,a)} = q_{(i,a)}/\bar{q}_{(i,a)}$. It is assumed that production and shipments are equal under normal conditions (i.e., $\bar{y}_{(i,a)} = \bar{q}_{(i,a)}$). Then, $\hat{q}_{(i,a)}$ is determined as follows:

$$\hat{q}_{(i,a)} = \min\left\{1, \hat{y}_{(i,a)} + \hat{s}^p_{(i,a)}\right\}.$$

This equation indicates that when production ($\hat{y}_{(i,a)}$) decreases due to supply constraints, shipments can be supplemented by the product inventory ($\hat{s}^p_{(i,a)}$), but only up to the normal shipment value as the maximum limit.

Under these assumptions, production is determined as follows:

$$\hat{y}_{(i,a)} = \min\left\{1, \min\left\{\sum_{j\in J} \bar{\omega}_{(j,b)\to(i,a)}\hat{q}_{(j,b)} + \hat{s}^m_{b\to(i,a)}\right\}_{b\in B(i,a)}\right\}.$$

When inventories are taken into account, the supply of intermediate goods from supplier firms is determined based on shipments rather than production. Consequently, procurement from each supplier is expressed as $\bar{\omega}_{(j,b)\to(i,a)}\hat{q}_{(j,b)}$. Furthermore, in the event of a decrease in supply from supplier firms, the shortfall can be compensated by utilizing material inventory ($\hat{s}^m_{b\to(i,a)}$).

(Model Solution)

In the simulation, the overall production decline rate of the manufacturing sector is calculated for each of the 321 bottleneck products identified in the previous subsection in the event of a supply constraint. This requires repeatedly calculating the cascading impact of supply constraints in bottleneck products, as they suppress the production of other firms and products through both direct and indirect transactional relationships. The specific algorithm is as follows.

Step 1: Initial Values

Let the bottleneck product subject to supply constraints be product c manufactured by firm k, and reduce the production of this product by $100 \times \epsilon\%$, i.e., $\hat{y}^0_{(k,c)} = 1 - \epsilon$. For instance, if production is represented on an annual basis, ϵ corresponding to a one-month production halt would be $1/12$. The production of products other than product c is not subject to constraints; hence, their initial value is set to 1. Accordingly, the initial values are summarized as follows:

$$\hat{y}^0_{(i,a)} = \begin{cases} 1 - \epsilon & if\ (i,a) = (k,c) \\ 1 & otherwise. \end{cases}$$

Step 2: Updating Process

Let the value after the n-th iteration denoted as $\hat{y}^n_{(i,a)}$. Then, $\hat{y}^n_{(i,a)}$ can be derived as follows:

$$\hat{y}^n_{(i,a)} = \begin{cases} 1 - \epsilon \quad if\ (i,a) = (k,c) \\ \min\left\{1, \min\left\{\sum_{j \in J} \overline{\omega}_{(j,b)\to(i,a)} \hat{q}^{n-1}_{(j,b)} + \hat{s}^m_{b\to(i,a)}\right\}_{b \in B(i,a)}\right\} \quad otherwise, \end{cases}$$

where $\hat{q}^{n-1}_{(j,b)}$ is denoted by;

$$\hat{q}^{n-1}_{(j,b)} = \min\left\{1, \hat{y}^{n-1}_{(j,b)} + \hat{s}^p_{(j,b)}\right\}.$$

Step 3: Iteration

Repeat Step 2 until $\hat{y}^n_{(i,a)}$ converges[28].

(Parameters)

First, the procurement amount from each supplier ($\bar{x}_{(j,b)\to(i,a)}$), necessary to compute the procurement ratio for each intermediate good ($\overline{\omega}_{(j,b)\to(i,a)}$), was determined by multiplying the firm-product-level transaction share estimated in Section 2 ($w_{(j,b)\to(i,a)}$) by the annual shipment value of firm j ($\bar{q}_j$). The value of $\bar{q}_j$ was obtained from the annual shipment value provided in the microdata of the ABS (principally, the value for 2023, the same applies hereafter). Given these values, $\overline{\omega}_{(j,b)\to(i,a)}$ was calculated based on its definition

[28] The convergence criterion is defined as $\sum_{(i,a)\in U} \left|\hat{y}^{n-1}_{(i,a)} - \hat{y}^n_{(i,a)}\right| < 0.01$, where U represents the entire set of firm-product pairs.

in Equation (2).

Next, product inventory ($\hat{s}^{p}_{(i,a)}$) was calculated by dividing the product inventory value (as of the beginning of the year) derived from the microdata of the ABS by the annual shipment value for each product category[29]. For material inventories ($\hat{s}^{m}_{b\to(i,a)}$), where product-specific data is unavailable, it was assumed that a firm's material inventory is uniformly distributed across all product categories ($\hat{s}^{m}_{b\to(i,a)} = \hat{s}^{m}_{b'\to(i,a')}\ \forall a, a' \in A(i);\ \forall b \in B(i,a); \forall b' \in B(i,a')$ where $A(i)$ denotes the set of all products produced by firm i). Under this assumption, the material inventory ($\hat{s}^{m}_{b\to(i,a)}$) was calculated by dividing the material inventory value (as of the beginning of the year) by the annual material usage, both obtained from the microdata of the b[30,31]. Calibrating inventory levels for each firm using actual inventory data is a distinguishing feature of this study and is not observed in prior research.

(Simulation Results)

In the simulation, the impact on gross production is computed for each bottleneck product in the event of a 50% reduction in production capacity. Specifically, using the algorithm described above, the impact on the annual production of each firm-product pair ($\hat{y}^{n}_{(i,a)}$) is calculated by assuming that the production of a bottleneck product (product c of firm k) is halved for m months, with $\epsilon = 0.5 \times m/12$. Following this, the production decline rate for each firm-product pair in the m-th month is determined as the difference between the annual production decline rates under the m-month shock and the $m-1$-month shock. The dynamics of the impact of supply constraints, as derived in this way, depend on the inventory levels of each firm and product. In other words, as production and shipments decline sequentially, beginning with firms and products that have depleted their inventory, the overall decline in manufacturing output expands over time.

[29] For missing values, imputation was performed using the values from the firm-product pair within the same product category that had the closest shipment value. If imputation could not be completed in this manner, the overall median was used to complete the imputation process.

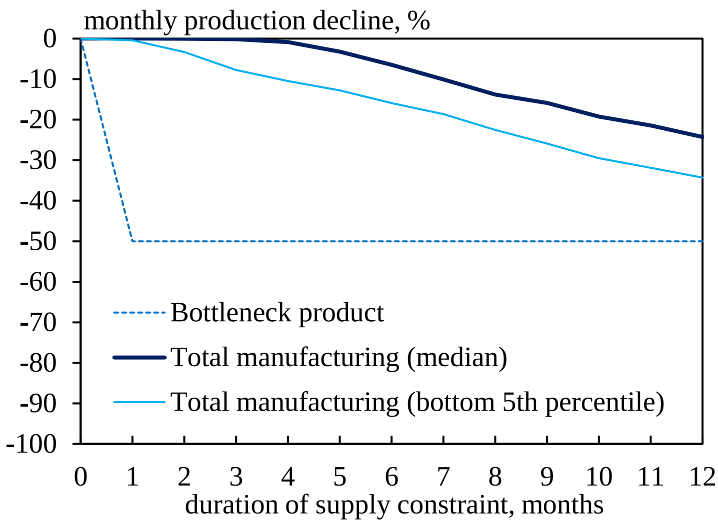
[30] For missing values, imputation was carried out using the value of the firm with the closest shipment value within the same industry (4-digit level). For any values that could not be imputed in this manner, the overall median was used to complete the imputation process.

[31] It is worth noting that the ABS also provides information on work-in-process inventories. However, this simulation does not utilize data on work-in-process inventories, as the model does not take such inventories into account. Additionally, the lack of critical information—such as the additional materials needed to convert work-in-process goods into finished products or the time required to complete the process—is another reason why work-in-process inventories are not considered here.

Figure 13 presents the results of simulations conducted on the 321 bottleneck products, calculating the production decline rate for the overall manufacturing sector. The figure displays the median and the 5th percentile. Starting with the median, it is evident that inventory-related mitigating effects help sustain macro-level production for approximately four months. However, if supply constraints extend beyond this period, firm inventories are gradually exhausted, leading to a more pronounced impact on macro-level production. In the 5th percentile case, the mitigating effects of inventories appear to dissipate by the second month, after which macro-level production begins to decline. These findings indicate that the impact of supply constraints on bottleneck products varies significantly, with the potential for substantial macro-level production effects to appear relatively early in certain scenarios.

The results of this study cannot be directly compared with those of similar prior research, such as Inoue and Todo (2019), due to differences in the underlying assumptions of the simulations. Nonetheless, both studies highlight a shared finding: supply constraints at certain firms can have exceptionally large indirect effects. As Inoue and Todo (2019) point out, the magnitude of these indirect effects is likely attributable to the assumption of non-substitutability among input factors and the pronounced heterogeneity in the centrality of individual firms (and products) within the network.

(Figure 13) Impact of Supply Constraints of Bottleneck Products on Total Manufacturing Production

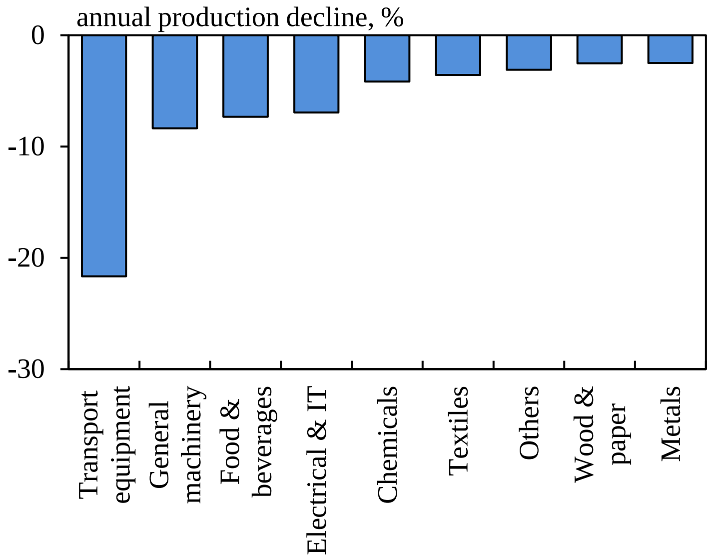


Note: "Total manufacturing (median)" represents the median rate of decline in total manufacturing production if the production of each bottleneck product decreases by 50%. The same applies to "Total manufacturing (bottom 5th percentile)."
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

A sectoral comparison reveals that the "Transportation Equipment" sector is the most vulnerable to supply constraints in bottleneck products (Figure 14). In the previous subsection, it was noted that there are relatively few intermediate goods classified as bottleneck products within the "Transportation Equipment" sector itself. However, as highlighted in Section 3, this sector has an extensive supply chain and depends on a wide variety of parts sourced from industries outside the transportation equipment sector. This reliance makes it particularly susceptible to the impacts of supply constraints in bottleneck products.

Furthermore, a comparison of the impact of bottleneck products with that of other products reveals that supply constraints on bottleneck products have a significantly larger effect, as illustrated in the left panel of Figure 15. Moreover, as shown in the right table of Figure 15, these differences in impact remain statistically significant even after controlling for factors such as shipment share and position within the supply chain (relative upstreamness). These findings indicate that the bottleneck products identified in this study successfully capture products with high potential impacts from supply constraints.

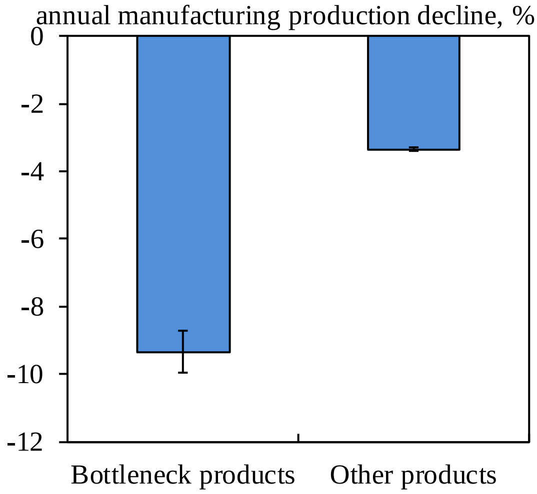
(Figure 14) Impact of Supply Constraints of Bottleneck Products by Industry



Note: The figure shows the median annual production decline rate for each industry if the production of each bottleneck product decreases by 50% over the course of one year. Electrical & IT: Electrical machinery, information and communication machinery, electronic components and devices. General machinery: General-purpose, production, and business-use machinery. Chemicals: Chemicals, plastics, petroleum and coal, and rubber. Metals: Steel, non-ferrous metals, and metal products. Wood & paper: Wood and wood products, paper and pulp, and printing. Textiles: Textiles and leather.
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

(Figure 15) Impact of Bottleneck Products: Comparison with Other Products

(Impact on Total Manufacturing)



(Controlling for Other Variables)

	Annual manufacturing production change (%)
Constant	11.00***
	(0.20)
Bottleneck dummy	-3.58***
	(0.34)
Sales share (%)	-0.06***
	(0.00)
Relative upstreamness	-29.00***
	(0.43)
Observations	28,388
R-squared	0.196

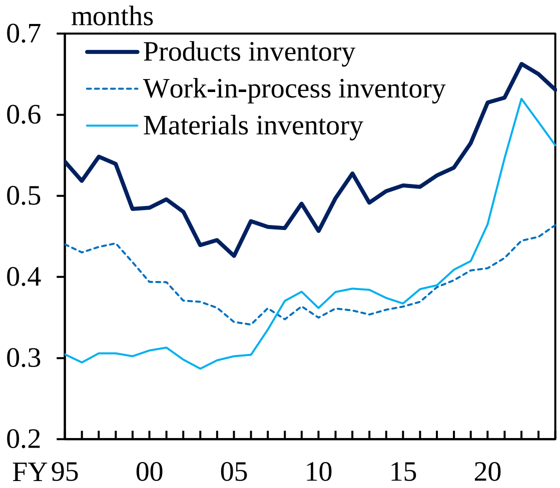
Notes: 1. The left figure calculates the annual production decline rate for total manufacturing in response to a year-long 50% production reduction shock for all firm-product pairs, and then computes the average values separately for bottleneck products and other products. The error bands represent the 95% confidence intervals.
2. In the multiple regression shown in the right table, the dependent variable is the overall manufacturing production change rate (%) at the 12th month in response to a year-long 50% production reduction shock for each firm-product pair. The bottleneck dummy is a binary variable that takes the value of 1 if the product is a bottleneck product. The sales share represents the proportion (%) of a firm-product pair's sales relative to the total sales of the same product category. The relative upstreamness (upstreamness / (upstreamness + downstreamness)) is a product-specific value calculated from the input-output structure at the basic sector classification in the *Input-Output Tables* (limited to the manufacturing sector). The values in parentheses indicate robust standard errors.

Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

(Inventory as a Mitigation Measure)

As we have seen so far, maintaining inventories can be an effective measure to some extent in mitigating the impact of short-term supply constraints. In fact, looking at the inventory rate of Japan's manufacturing sector, it has followed a downward trend since the late 1990s, driven by advancements in inventory management aimed at reducing inventory costs. However, since the 2010s, reflecting repeated supply constraints caused by natural disasters and similar events, there has been a strategic buildup of inventories for materials and components. As a result, over the past decade, the inventory ratio has shown a clear upward trend (Figure 16).

(Figure 16) Inventory Ratio



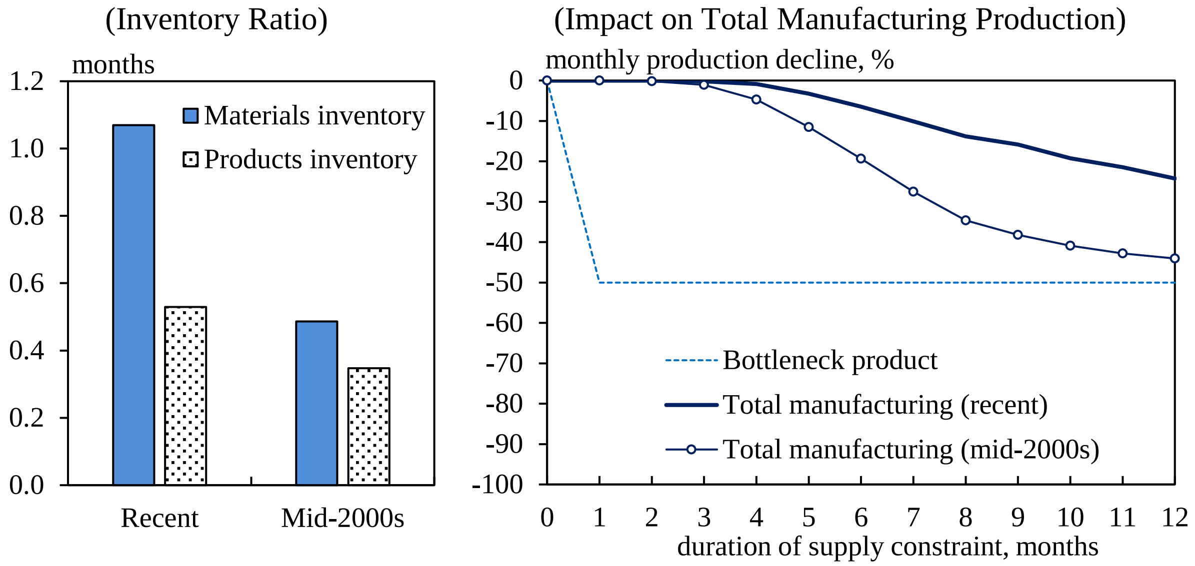
Note: Inventory ratio = Inventory balance / Sales. The figures represent all manufacturing industries and enterprise scales, calculated based on the *Financial Statements Statistics of Corporations by Industry (Annual Report).*
Source: Ministry of Finance.

Below, we examine the extent to which this buildup of inventories has strengthened the resilience of Japan's manufacturing supply chains. Specifically, we compare the results of the previous simulation with those obtained using, instead, the inventory ratio of the mid-2000s[32], a period when inventory levels were largely at their lowest point.

As shown in Figure 17, the simulation results indicate that the impact of supply constraints on production, assuming the inventory levels of the mid-2000s, is significantly greater compared to the recent ones. Furthermore, due to the lower inventory levels across firms and products during that period, supply constraints propagated more quickly between firms, leading to a faster pace of production decline. These findings suggest that, based on repeated natural disaster experiences, such as the Great East Japan Earthquake, efforts by firms to increase inventory levels, while raising inventory holding costs, have helped enhance the ability of individual firms to sustain production under short-term supply constraints. This has contributed to strengthening the overall resilience of Japan's manufacturing supply chains, provided other conditions remain constant. It should be noted that this analysis does not consider the potential change in supply chain structures between the present and the mid-2000s.

[32] The product inventory ratios and material inventory ratios were derived from the microdata of the *2007 Census of Manufactures*. However, as corporate numbers were not included in the dataset, the following approach was adopted to estimate past inventory rates for each firm. For product inventories, the product inventory ratio (as of 2006) from the firm-product pair with the same product classification number and the closest shipment value was used. For material inventories, the material inventory ratio (as of 2006) from the firm within the same detailed industry classification and with the closest total shipment value of products was used.

(Figure 17) Inventory Level and Supply Chain Resilience



Note: "Recent" refers to the beginning of 2023 in principle, while "Mid-2000s" refers to the beginning of 2006. In the left panel, the inventory ratio is defined as follows: Products inventory ratio = Products inventory / Sales; Materials inventory ratio = Materials inventory / Material costs. Both are the median values. The right panel illustrates the results of two simulations (median values) showing the effects of changes in inventory ratios between the "Recent" period and the "Mid-2000s."
Sources: Teikoku Databank; Ministry of Internal Affairs and Communications; Ministry of Economy, Trade and Industry.

5. Conclusion

This paper provides a high-resolution visualization of the structure of Japanese manufacturing supply chains by integrating detailed firm-to-firm transaction data with firm-level data of manufactured products.

The findings of this study can be summarized in the following three points.

First, this study showed quantitatively that supply chains of automobile manufacturers are characterized by their exceptional length and scale. Furthermore, the analysis suggested that demand fluctuations originating from these focal firms could exert a greater impact on the production activities of individual suppliers compared to focal firms in other industries.

Second, the analysis revealed that within multilayered supply chains, numerous bottleneck products exist that can have significant effects when supply shocks occur. In particular, the automotive industry, with its long and extensive supply chains, is significantly impacted by supply constraints on such bottleneck products. Additionally, it was suggested that maintaining inventories can serve as a partially effective measure for mitigating the effects of these supply constraints.

Third, the study demonstrated that concepts such as centrality and average propagation lengths (APL) are valuable for visualizing manufacturing supply chains. Specifically, by employing authority centrality, focal firms positioned at the very downstream end of supply chains were successfully identified. Moreover, the combination of these focal firms and APL facilitated the identification of the hierarchical structure of supply chains. The identification of bottleneck products using betweenness centrality also successfully detected multiple products that have previously been responsible for widespread supply constraints.

Despite the limitations in data quality and coverage, the highly granular firm-product-level production network data constructed in this paper is considered valuable and has the potential to be used to analyze corporate behavior through supply chains. Future research should refine the network data further and broaden the scope of analysis to accurately monitor macroeconomic developments.

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Appendix 1. Firm-Product-Level Production Networks

This appendix details the methodology for constructing firm-product-level production networks by integrating the Transaction Share Data from Teikoku Databank, firm-level data of manufactured products derived from the microdata of the *Annual Business Survey* (hereafter ABS) conducted by the Ministry of Internal Affairs and Communications (MIC) and the Ministry of Economy, Trade and Industry (METI), and the input-output structure between products obtained from the *Input-Output Tables* published by the MIC.

1. Definition of Firm-to-Firm Transaction Networks

To begin, we formulate the firm-to-firm transaction network as a weighted directed graph $\mathcal{G}(V, E, w)$. The elements that constitute the network are given follows:

I. $V = \{v_1, v_2, \dots, v_{N_f}\}$ represents the entire set of firms, where N_f denotes the total number of firms.

II. $E \subseteq V \times V$ represents a set of directed edges, where there is a transactional relationship from firm v_s to firm v_c if $(v_s, v_c) \in E$. In the transactional relationship, v_s and v_C are called a supplier and a customer, respectively.

III. w is a mapping from the set E to the real numbers, and it is referred to as the weight function. The weight function returns $w(v_s, v_c) > 0$ if $(v_s, v_c) \in E$. The value of $w(v_s, v_c)$ corresponds to the share of the supplier v_s's total sales accounted for by the sales to the customer firm v_c (transaction share), which is obtained from the Transaction Share Data.

We define the adjacency matrix $W = [w_{v_s, v_c}]_{s,c=1,\dots,N_f}$ as follows:

$$w_{v_s,v_c} = \begin{cases} w(v_s, v_c) & if\ (v_s, v_c) \in E \\ 0 & otherwise. \end{cases}$$

2. Definition of Each Firm's Products

Next, we define the set of products manufactured by each firm and their respective shipment values.

First, the set of products produced by a given firm $v_i (\in V)$ is defined as $P_i = \{p_{i,1}, p_{i,2}, \dots, p_{i,N_{i,p}}\}$, which is obtained from the ABS microdata. Each element $p_{i,j} \in P_i$ represents a specific product produced by firm v_i. $N_{i,p}$ denotes the total number of firm v_i's products.

The set of shipment values corresponding to each product produced by firm v_i is defined as $Y_i = \left\{y_{i,1}, y_{i,2,}, \ldots, y_{i,N_{i,p}}\right\}$. Here, each element $y_{i,j} \in Y_i$ represents the shipment value of a specific product produced by firm v_i, which is obtained from the ABS microdata.

3. Construction of Firm-Product-Level Production Networks

Finally, we calculate the transaction share $w_{(v_s,p_{s,j}) \to (v_c,p_{c,k})}$ between a given supplier-product pair $(v_s, p_{s,j})$ and customer-product pair $(v_c, p_{c,k})$. Here, the transaction share $w_{(v_s,p_{s,j}) \to (v_c,p_{c,k})}$ represents the proportion of the sales of product $p_{s,j}$ by supplier firm v_s to customer firm v_c for the production of product $p_{c,k}$, relative to the total sales of supplier firm v_s.

Specifically, the firm-to-firm transaction share, w_{v_s,v_c}, which is an element of the adjacency matrix, is allocated in the following manner to estimate the transaction share between firm-product pairs $w_{(v_s,p_{s,j}) \to (v_c,p_{c,k})}$.

$$w_{(v_s,p_{s,j}) \to (v_c,p_{c,k})} = \theta_{(v_s,p_{s,j}) \to (v_c,p_{c,k})} \times w_{v_s,v_c} \qquad \text{(A1)}$$

The weight parameter $\theta_{(v_s,p_{s,j}) \to (v_c,p_{c,k})}$ is defined in the following equation using the three factors $\left(\theta^{(1)}_{v_s,p_{s,j}}, \theta^{(2)}_{v_c,p_{c,k}}, \theta^{(3)}_{p_{s,j},p_{c,k}}\right)$:

$$\theta_{(v_s,p_{s,j}) \to (v_c,p_{c,k})} = \frac{\theta^{(1)}_{v_s,p_{s,j}} \times \theta^{(2)}_{v_c,p_{c,k}} \times \theta^{(3)}_{p_{s,j},p_{c,k}}}{\sum_{p_{s,j} \in P_s} \sum_{p_{c,k} \in P_c} \theta^{(1)}_{v_s,p_{s,j}} \times \theta^{(2)}_{v_c,p_{c,k}} \times \theta^{(3)}_{p_{s,j},p_{c,k}}},$$

where $\theta^{(1)}_{v_s,p_{s,j}}$、 $\theta^{(2)}_{v_c,p_{c,k}}$、 $\theta^{(3)}_{p_{s,j},p_{c,k}}$ are defined as;

$$\theta^{(1)}_{v_s,p_{s,j}} = \frac{y_{s,j}}{\sum_{p_{s,j} \in P_s} y_{s,j}},$$

$$\theta^{(2)}_{v_c,p_{c,k}} = \frac{y_{c,k}}{\sum_{p_{c,k} \in P_c} y_{c,k}}, \text{ and}$$

$$\theta^{(3)}_{p_{s,j},p_{c,k}} = \frac{Z_{p_{s,j},p_{c,k}}}{\sum_{p_{s,j} \in P_s} Z_{p_{s,j},p_{c,k}}}.$$

The case where the denominator becomes zero is defined as follows:

$$\sum_{p_{s,j} \in P_s} Z_{p_{s,j},p_{c,k}} = 0 \Rightarrow \theta^{(3)}_{p_{s,j},p_{c,k}} = 0 \; and$$

$$\sum_{p_{s,j} \in P_s} \sum_{p_{c,k} \in P_c} \theta^{(1)}_{v_s,p_{s,j}} \times \theta^{(2)}_{v_c,p_{c,k}} \times \theta^{(3)}_{p_{s,j},p_{c,k}} = 0 \Rightarrow \theta_{(v_s,p_{s,j}) \to (v_c,p_{c,k})} = 0.$$

Here, $Z_{p_{s,j},p_{c,k}}$ is an element of the intermediate input matrix Z, representing the intermediate input value of product $p_{s,j}$ required for the production of one unit of product $p_{c,k}$. The intermediate input matrix Z is based on the input table of the basic sector classification from the *Input-Output Tables*.

$\theta^{(1)}_{v_s,p_{s,j}}$ represents the share of product $p_{s,j}$ in the total shipment value of supplier v_s, while $\theta^{(2)}_{v_c,p_{c,k}}$ represents the share of product $p_{c,k}$ in the total shipment value of customer v_c. Additionally, $\theta^{(3)}_{p_{s,j},p_{c,k}}$ indicates the relative importance of product $p_{s,j}$ among the products produced by supplier v_s, as an intermediate input for the production of product $p_{c,k}$[33].

Therefore, the framework is designed so that (i) transactions involving major products with a high shipment share at either the supplier or customer firm, and (ii) transactions between products with strong input relationships have higher transaction shares. On the other hand, the transaction share between products with no input relationship in the *Input-Output Tables* (i.e., $Z_{p_{s,j},p_{c,k}} = 0$) is set to zero, which implies that the estimated network excludes transactions unrelated to intermediate inputs (e.g., as capital goods purchases).

4. Reaggregated Network at the Firm Level

When the estimated firm-product-level production network is reaggregated to the firm level, it is represented as the adjacency matrix $\widetilde{W} = \left[\widetilde{w}_{v_s,v_c}\right]_{s,c=1,\dots,N_f}$, which is used in Section 3 for identifying focal firms and other analytical purposes. In this representation, each element $\widetilde{w}_{v_s,v_c}$ of the adjacency matrix $\widetilde{W}$ is written as follows.

$$\widetilde{w}_{v_s,v_c} = \sum_{p_{s,j} \in P_s} \sum_{p_{c,k} \in P_c} w_{(v_s,p_{s,j}) \to (v_c,p_{c,k})}$$

[33] One of the product classifications in the ABS is "resale revenue." This refers to situations where products manufactured by a subsidiary are delivered in bulk to the parent company, and then sold to other companies. In this study, when a customer earns resale revenue and both the supplier firm and the customer firm ship the same product, it is assumed that the resale revenue is attributed to that specific product. The transaction share corresponding to the resale transaction is determined as follows: first, the resale revenue is allocated to individual products proportionally based on the shipment value ratio by product at the customer, thereby estimating the resale value for each product. Then, the transaction share is calculated in the same manner as for regular transactions, using Equation (A1). In this calculation, we set $\theta^{(3)}_{p_{s,j},p_{c,k}} = 1$.

Appendix 2. A Model Incorporating Supply Constraints on Imported Goods

This appendix extends the model constructed in Section 4 and presents a methodology for simulating the impacts of supply constraints on imported goods.

When considering imported goods, it is important to account for the fact that the substitutability between imported and domestic goods may differ depending on the product. Specifically, we categorize products into two types[34]: (i) products for which imported and domestic goods are substitutes, where the input for such products is represented as the sum of inputs of imported and domestic goods; and (ii) products for which imported and domestic goods are completely non-substitutable, where the input for such products is determined by the smaller of the inputs of imported and domestic goods. The set of products in category (i) is denoted as I^s, and the set of products in category (ii) is denoted as I^c.

(Details of the Model)

(1) The Case without Inventories

In a simple case where inventories do not exist, the production $\hat{y}(i,a)$ of product a by firm i is determined as follows:

$$\hat{y}_{(i,a)} = \min\{\hat{x}_{b\to(i,a)}\}_{b\in B(i,a)},$$

where $\hat{x}_{b\to(i,a)}$ represents the input of product b used in the production of product a by firm i (deviation rate from normal conditions). While this production function itself is identical to what is assumed in Section 4, when considering imported goods, it becomes necessary to distinguish $\hat{x}_{b\to(i,a)}$ based on the nature of product b (the substitutability between imported and domestic goods).

First, consider product $b \in B(i,a) \cap I^s$, where imported goods and domestic goods are substitutable. In this case, $\hat{x}_{b\to(i,a)}$ is defined as follows:

$$\hat{x}_{b\to(i,a)} = \sum_{j\in J\cup f} \overline{w}_{(j,b)\to(i,a)}\hat{y}_{(j,b)},$$

where f represents the entirety of overseas entities, and $\hat{y}_{(f,b)}$ denotes the imports of

[34] In general, materials such as petroleum and coal products, as well as basic petrochemicals, are thought to exhibit a certain degree of substitutability, whereas highly processed components are generally considered to be less substitutable. However, as will be discussed later, accurately defining such substitutability relationships requires verification based on data.

product b (deviation rate from normal conditions). Here, the input of imported goods is treated collectively as if it were supplied by a single entity. Additionally, $\overline{w}_{(j,b)\to(i,a)}$ represents the procurement ratio that accounts for the input of imported goods and is defined as follows:

$$\overline{w}_{(j,b)\to(i,a)} = \frac{\bar{x}_{(j,b)\to(i,a)}}{\sum_{j\in J\cup f} \bar{x}_{(j,b)\to(i,a)}},$$

where if $j = f$, $\overline{w}_{(f,b)\to(i,a)}$ represents the import ratio of product b used by firm i in the production of product a. On the other hand, if $j \neq f$, as shown in the following equation, it is calculated by multiplying $\overline{\omega}_{(j,b)\to(i,a)}$, which is defined in Section 4, by the domestic procurement ratio $1 - \overline{w}_{(f,b)\to(i,a)}$:

$$\overline{w}_{(j,b)\to(i,a)} = \left(1 - \overline{w}_{(f,b)\to(i,a)}\right) \times \overline{\omega}_{(j,b)\to(i,a)},$$

where if there is no domestic input for product b at all (i.e., $\bar{x}_{(j,b)\to(i,a)} = 0 \;\; \forall\, j \in J$), then $\hat{x}_{b\to(i,a)} = \left(1 - \overline{w}_{(f,b)\to(i,a)}\right) \times 1 + \overline{w}_{(f,b)\to(i,a)} \times \hat{y}_{(f,b)}$.

Next, consider product $b \in B(i,a) \cap I^c$, where imported goods and domestic goods are non-substitutable. In this case, $\hat{x}_{b\to(i,a)}$ is defined as follows:

$$\hat{x}_{b\to(i,a)} = \min\left\{\hat{x}^d_{b\to(i,a)}, \hat{x}^f_{b\to(i,a)}\right\},$$

where $\hat{x}^d_{b\to(i,a)}$ represents the input of domestic goods for product b (deviation rate from normal conditions), while $\hat{x}^f_{b\to(i,a)}$ represents the input of imported goods for product b (deviation rate from normal conditions). Therefore, for products where imported and domestic goods are non-substitutable, the input of the product is determined by the larger reduction rate between the domestic goods input and the imported goods input.

$\hat{x}^d_{b\to(i,a)}$ is calculated in the same way as in the case where there is no imported input, as shown in the following equation:

$$\hat{x}^d_{b\to(i,a)} = \sum_{j\in J} \overline{\omega}_{(j,b)\to(i,a)} \hat{y}_{(j,b)}.$$

On the other hand, $\hat{x}^f_{b\to(i,a)}$ is equal to the import of product b (the deviation rate from normal times). That is, it is expressed as follows:

$$\hat{x}^f_{b\to(i,a)} = \hat{y}_{(f,b)},$$

where, for product b, if there is no imported input, $\hat{x}^{f}_{b\to(i,a)} = 1$. Similarly, if there is no domestic input, $\hat{x}^{d}_{b\to(i,a)} = 1$.

To summarize, the input of product b used for the production of product a by firm i (i.e., $\hat{x}_{b\to(i,a)}$) has the following properties:

1. For products where imported inputs and domestic inputs are substitutable, $\hat{x}^{f}_{b\to(i,a)}$ becomes a weighted average of the supply of imported goods and the supply of domestic goods.

2. For products where imported inputs and domestic inputs are not substitutable, $\hat{x}^{f}_{b\to(i,a)}$ is determined by whichever supply, imported or domestic, is smaller.

Furthermore, the production $\hat{y}_{(i,a)}$ of product a by firm i is determined by the input of item b (i.e., $\hat{x}_{b\to(i,a)}$), which has the largest reduction rate among the inputs required for production.

(2) The Case with Inventories

In the case where inventory exists, the shipment of product b by firm j (the deviation rate from normal times) is defined as follows:

$$\hat{q}_{(j,b)} = \min\left\{1, \hat{y}_{(j,b)} + \hat{s}^{p}_{(j,b)}\right\},$$

where $\hat{s}^{p}_{(j,b)}$ represents the product inventory divided by the normal production level, and in the case of imported goods, $\hat{s}^{p}_{(f,b)} = 0$.

$\hat{x}_{b\to(i,a)}$ is redefined as follows:

$$\hat{x}_{b\to(i,a)} = \begin{cases} \sum_{j\in J\cup f} \overline{w}_{(j,b)\to(i,a)}\hat{q}_{(j,b)} & if\ b \in B(i,a) \cap I^{s} \\ \min\left\{\hat{x}^{d}_{b\to(i,a)}, \hat{x}^{f}_{b\to(i,a)}\right\} & if\ b \in B(i,a) \cap I^{c}, \end{cases}$$

where $\hat{x}^{d}_{b\to(i,a)}$ and $\hat{x}^{f}_{b\to(i,a)}$ are also redefined as follows:

$$\hat{x}^{d}_{b\to(i,a)} = \sum_{j\in J} \overline{\omega}_{(j,b)\to(i,a)}\hat{q}_{(j,b)}$$

$$\hat{x}^{f}_{b\to(i,a)} = \hat{q}_{(f,b)} = \hat{y}_{(j,b)},$$

where, for product b, if there is no imported input, $\hat{x}^{f}_{b\to(i,a)} = 1$. Similarly, if there is no domestic input, $\hat{x}^d_{b\to(i,a)} = 1$.

The production of product a by firm i is determined as follows:

$$\hat{y}_{(i,a)} = \min\left\{1, \min\left\{\hat{x}_{b\to(i,a)} + \hat{s}^m_{b\to(i,a)}\right\}_{b\in B(i,a)}\right\},$$

where $\hat{s}^m_{b\to(i,a)}$ represents the material inventory of product b used for the production of product a by firm i, divided by the material input amount at normal times.

(Parameters)

The introduction of imported products necessitates defining the import ratio $\overline{w}_{(f,b)\to(i,a)}$. Since data on import ratios at the firm-product level is unavailable, we assume that the import ratios for the same product pair are identical across all firms. Specifically, $\overline{w}_{(f,b)\to(i,a)} = \overline{w}_{(f,b)\to a}\ \forall i$. Under this assumption, the value of $\overline{w}_{(f,b)\to a}$ is determined using the import ratio of product b in the input for product a, which is provided in the basic sector classification of the *Input-Output Tables*.

Furthermore, for each product, it is necessary to determine the substitution relationship between imported and domestic products—that is, to predefine whether each product belongs to set I^s or set I^c. Ideally, these relationships should be established by estimating the elasticity of demand for imported and domestic products based on available data. However, in practice, such an approach may be impossible due to data limitations and other constraints. Therefore, practical alternatives may involve uniformly setting the substitution relationship for all products regardless of their specific characteristics or defining it based on the analyst's judgment.

(Considerations for the Simulation)

Based on the framework established above, it is possible to simulate the impact of a supply shock, such as a reduction in imported products, on domestic production. However, several considerations must be taken into account when interpreting the results of this simulation.

First, due to data limitations, this analysis assumes that the import ratio for the same product pair remains constant across all firms. In reality, even within firms producing the same product, some may rely heavily on imported materials, while others may primarily source materials domestically. This heterogeneity is not accounted for in the current framework. Furthermore, the analysis does not consider the possibility of firms sourcing substitutes from other regions in response to a decline in imports from a specific region. Improving the analytical framework to incorporate these factors is an important area for future research.